Studies into State-dependent Asset Pricing Models and Dynamic Asset Allocation in International Equity Markets

A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

Roksana Hematizadeh

Master of Business Administration in Finance, Multimedia University
Bachelor of Statistics, Shiraz University

School of Economics Finance and Marketing

College of Business

RMIT University

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Declaration of Originality

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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List of Conference Publications Relevant to This Thesis

- A research paper titled "Stock market volatility and new information: Evidence from emerging markets", developed as a part of the thesis output, was presented at the Financial Markets and Corporate Governance Conference, 8–10 April 2015, Curtin University, Perth, Australia. PhD Symposium.
- A research paper titled "Volatility in emerging markets using Markov switching framework", developed as a part of the thesis output, was presented at the Financial Markets and Corporate Governance Conference, 30 March–1 April 2016, Monash University, Melbourne, Australia. Main Conference.
- A research paper titled "Volatility in emerging markets using Markov switching framework", developed as a part of the thesis output, was accepted for the AFAANZ Conference on the Gold Coast, Australia, July 3–5, 2016. Main Conference.
- A research paper titled "Dynamic Asset Allocation in Diverse Financial Markets", developed from part of the thesis output, was presented at (both in main conferences):
    - the Annual Conference of the Multinational Finance Society, Bucharest, Romania, 25–28 June 2017.
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Abstract

One aspect of asset pricing research over the last five decades has focused on the application of asset pricing models to determine an optimal international equity portfolio. However, non-normality in equity market returns and time-varying correlation among international markets have made optimal portfolio selection difficult. For example, the observed high volatility phase in equity market returns is usually associated with extreme negative returns, which causes non-normality in the distribution of market returns. The objective of this thesis is to develop an appropriately fitted asset pricing model that explicitly captures this salient feature of equity market returns, and that exploits the potential diversification benefits of emerging markets. we use a state-dependent Markov model, which distinguishes between high and low volatility states, to capture time-varying returns in emerging market equity indices. The model is then extended into global asset allocation.

Time-varying volatility has been identified as a distinguishing feature in financial markets. Previous studies have characterized this feature as regime phases; typically, two regimes signifying bull markets and bear markets have been identified by time-variation in the market risk premium. In this thesis, we employ a state-dependent Markov framework and compare it with mean-variance portfolio optimization. we use time variation in the world market risk premium to identify market phases and study the explanatory power of the model during phase changes in emerging markets. we investigate the use of a macroeconomic variable as a state predictor and examine dynamic linkages between emerging market returns and the macroeconomic variable. we then implement these models in a dynamic asset allocation strategy for portfolio optimization.

First, we find that emerging markets exhibit time-varying volatility depending on the world market phases, and the state-dependent Markov models offer superior in-sample estimates of expected returns compared to alternative models. Second, the time-varying nature of asset returns potentially adds value to portfolio performance and provides diversification benefits for international investors. Third, the state-dependent model indicates that the downside risks of emerging markets will be offset by their outperformance during normal times. The outcomes of this thesis have practical implications for risk assessment of portfolios and asset allocation decisions across emerging markets.

Finally, we implement a dynamic asset allocation strategy and use emerging equity markets as an alternative asset class. Dynamic asset allocation enables investors and portfolio managers to hedge against risk by investing in safer asset classes such as cash and bonds during bad times, and to make optimal decisions during normal times by diversifying portfolios into different equity markets. we find that incorporating models that account for regime phases gives additional insights into return dynamics in emerging markets.

Keywords: Asset allocation, asset pricing, emerging equity markets, state-dependent Markov model

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List of Abbreviations

ADF	Augmented Dickey-Fuller
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
ASEAN	Association of Southeast Asian Nations
CAPM	Capital Asset Pricing Model
DCC-GARCH	Dynamic Conditional Correlation GARCH
EM	Expectation Maximization
EMH	Efficient Market Hypothesis
FTP	Fixed Transition Probability
FTSE	Financial Times Stock Exchange
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GJR-GARCH	Glosten, Jagannathan, and Runkle GARCH
GNI	Gross National Income
HQ	Hannan–Quinn information criterion
MM	Market Model
MSCI	Morgan Stanley Capital International
MVE	Mean-variance Efficient
NBER	National Bureau of Economic Research
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
SC	Schwarz Information Criterion
SD International CAPM	State-dependent International Capital Asset Pricing Model
SDMM	State-dependent Markov Model
T-bill	Treasury bill
TFD	Thomson Reuters Financials DataStream
TVTP	Time-varying Transition Probability
UAE	United Arab Emirate
US	United States
USD	United States Dollar
VaR	Value-at-Risk

Chapter 1 Introduction

1.1 Rationale

The growth and development of international financial markets over the last three decades has made these markets more easily accessible and a more viable option for international diversification and global investment. However, the allocation of funds among diverse financial markets is a challenging issue for international investors and portfolio managers, especially in extreme conditions such as the 2008 financial crisis. While mean-variance portfolio optimization based on historical data has been the most widely accepted method used in international equity portfolio diversification, the time-varying nature of asset returns leads to non-normality in return distributions and makes identification of optimal portfolios problematic. Additionally, heterogeneity in time variation across financial markets causes time-varying correlations among international markets.

While most international portfolio allocation focuses on developed markets, emerging markets such as those in Brazil, China and India are seen to offer enormous investment opportunities.[1] Emerging equity market returns tend to be characterized by higher volatility and a different degree of correlation with the world equity market. Although the liberalization wave which began in the early 1990s has increased the degree of integration, these markets remain substantially segmented from the world market and represent an opportunity to enhance risk-adjusted returns in a portfolio. Moreover, the degree of correlation is time-varying; correlation increases in a time of crisis and returns to the initial levels after the crisis. Consistent with the prior literature, two dominant phases are identified in market returns, known as "bull" and "bear" phases, each with different characteristics[2] regarding returns, volatility and the degree of correlation, and providing different investment opportunities.

This thesis contributes to the research on international portfolio diversification by using a Markov-switching framework to explicitly account for the time-varying nature of asset returns and

[1] In this study, we select emerging markets based on Morgan Stanley Capital International (MSCI) classification scheme. MSCI emerging market indices include 23 countries in four geographic regions as follows: the Americas (Brazil, Chile, Colombia, Mexico and Peru), Asia Pacific (China, India, Indonesia, Malaysia, Philippines, Taiwan, Thailand and South Korea), Europe (Greece, Czech Republic, Hungary and Poland) and West Asia and Africa (Egypt, Qatar, Russia, South Africa, Turkey and United Arab Emirate). The criterion for MSCI classification is based on country's economic development, size and liquidity and market accessibility or openness to foreign ownership.

[2] International financial markets are usually characterized by episodes of low volatility and higher returns (bull market) and episodes of high volatility and lower returns (bear market). Previous research shows that correlation between international markets increase during bear markets.

incorporates emerging equity markets into the analysis of market investment and asset allocation.

1.2 Asset Pricing Models

The Capital Asset Pricing Model (CAPM) was developed to explain cross-sectional variation in asset returns, or in other words, how risky assets are priced in the marketplace (Sharpe, 1964). The model remains a core benchmark in asset pricing and portfolio theory despite its limitations. Its main weaknesses are that it assumes a linear and stable relationship between asset returns and the market risk premium, as well as time-invariant asset betas, and that only market related risk is priced. Dissatisfaction with the results of empirical tests of the model led to the development of several alternatives (Fama & French, 1992).[3] In further research, Fama and French (2015) designed a model with additional factors to make up for this shortcoming.

According to the CAPM, an asset's expected return is proportional to its market beta, which holds constant between periods of high and low market returns. The CAPM assumes that the distribution of an asset's return is symmetrical, and that the downside and upside betas for an asset are the same. However, due to non-normality in the distribution of asset returns (asymmetric behaviour of risk), it is important to differentiate between downside and upside risk. For example, Bawa and Lindenberg (1977) modified the CAPM by replacing the standard beta with a downside beta, which takes into account the asymmetric behaviour of risk during market downturns.

One practical limitation of the CAPM model stems from time variation in the market risk premium, as the model cannot account for the time-varying nature of asset returns.[4] Further research indicates the importance of the time variation in market risk premium (Kim et al., 2004). A number of studies find that time-varying volatility in the equity risk premium and in betas are associated with different market phases (Abdymomunov & Morley, 2011; Chen, Lin, & Philip, 2012; Chen & Huang, 2007; Huang, 2000, 2003; Vendrame et al., 2018). Ramchand

[3] For example, previous research identifies that average returns on common stocks are associated with certain firm characteristics such as earning-price ratio (Basu, 1977), size factors (Banz, 1981), debt-equity ratios (Bhandari, 1988), liquidity (Amihud & Mendelson, 1986), book-to-market equity ratios (Rosenberg, Reid, & Lanstein, 1985), momentum effects (Jegadeesh & Titman, 1993), size and value risk factors (Fama & French, 1996). Because these patterns in average returns apparently are not explained by the CAPM, they are called anomalies (Fama & French, 1996).

[4] A strand of research addresses this issue with a new adjustment allowing betas and the market risk premium to vary over time (see e.g., Jagannathan and Wang (1996)). Along similar lines, Lewellen and Nagel (2006) find that the test of the conditional model does not explain asset-pricing anomalies and the estimates of covariance between betas and the market risk premium are too small to impose an important theoretical explanation.

and Susmel (1998) examine a conditional International CAPM, allowing market returns to depend on a world risk factor using a two-state Markov-switching model. This thesis adopts the approach of Kim et al. (2004) to measure structural changes in the market risk premium, and incorporates that into the study of the International CAPM. This enables different beta values to be used depending on the state of market volatility and has the potential to improve the estimation of expected returns. Market phases are identified based on high and low volatility states in the market risk premium.

Another strand of research argues that time-variation in asset returns is caused by macroeconomic influences. For example, Campbell and Ammer (1993) find that asset returns are driven by news about future excess returns, news about future inflation, and news about the short-term interest rate. Further studies find that interest rate fluctuations are associated with equity price movements and may also cause changes in the volatility level of equity returns (Basistha & Kurov, 2008; Bernanke & Kuttner, 2005; Brennan & Xia, 2001; Chen, 2007; Henry, 2009). To account for the effect of interest rate changes on asset returns, this thesis also adopts Filardo (1994) approach, assuming that the probability of switching is governed by some leading economic indicators. Filardo (1994) develops a Markov-switching model, assuming that the probability of switching may be governed by some leading economic indicators. He allows time-varying transition probabilities that are functions of underlying economic fundamentals to identify the business cycle. This thesis tests the validity of past findings for a conditional asset pricing model by using an alternative method to model time-varying betas, and to evaluate how the model can contribute to better explaining asset pricing.

1.3 Overview of Previous Studies

Equity returns, in general, are not normally distributed. This is particularly so in emerging markets because their return series departs from normality more than returns in developed markets do (Bekaert, Erb, Harvey, & Viskanta, 1998; Bekaert & Harvey, 1997; Canela & Collazo, 2007; Kittiakarasakun & Tse, 2011). For example, emerging markets present a higher level of kurtosis compared to developed markets, which implies that substantial shocks of either sign occur more often and that the return series are more likely to show non-normality (Celık, 2012; Chiang, Jeon, & Li, 2007). Given the distributional characteristics of returns, it is essential to account for this feature when assessing the risk and when diversifying a portfolio.

In general, equity market returns volatility demonstrates time-varying behaviour, with volatility (risk) increasing during market downturns and decreasing during market recovery[5] (Engle et al., 1987). Empirical evidence suggests that emerging markets are no exception to this (Al Janabi, Hatemi-J, & Irandoust, 2010; Esman Nyamongo & Misati, 2010). Because emerging market returns are skewed and have fat tails, time-varying volatility is of a particular type and is more pronounced in these markets.

When implementing an optimal international investment strategy, a model that captures this stylized feature of emerging market returns should be adopted. As their time-varying behaviour is different from that observed in developed markets, such a model offers potential additional return enhancement and diversification opportunities when constructing portfolios. This thesis examines whether an asset pricing model that captures time variation in market returns will improve understanding of emerging equity market returns and lead to better investment strategies.

1.4 Market Integration (Integration versus Segmentation)

Given that many emerging markets are not entirely liberalized, and are subject to many restrictions, they are more likely to experience higher volatility. Importantly, some studies corroborating this view have examined the impact of market liberalization and found that higher levels of market liberalization reduce overall stock returns volatility (Umutlu, Akdeniz, & Altay-Salih, 2010).[6]

Financial integration is defined as the free access of foreign investors to domestic financial markets and of domestic investors to foreign financial markets; otherwise, the market is segmented (Bekaert & Harvey, 2002). In contrast with integrated markets, where volatility is mainly driven by global factors, volatility in segmented markets[7] is mostly driven by country-specific factors (Bekaert & Harvey, 1997). The main elements that shape market integration are openness to foreign ownership, market development, and country political risk profile (Geert Bekaert, Campbell R Harvey, Christian T Lundblad, & Stephan Siegel, 2011). As mentioned in the literature, most emerging markets are significantly less integrated with global capital markets (Hanauer & Linhart, 2015). It is necessary to understand how the underpinnings

[5] The equity markets can be identified by higher uncertainty with lower returns (bear market) and lower uncertainty with higher returns (bull market).
[6] Although some studies produce mixed results; volatility after liberalization has been at different levels depending on whether volatility is driven by domestic factors or transmitted from developed markets (Hargis, 2002).
[7] These are sometimes called “disintegrated” markets (Berger & Pozzi, 2013).

of volatility behaviour and stock market co-movement can benefit international investors and portfolio managers in making informed decisions when diversifying their portfolio and hedging against risk.

Three quantitative methods have been introduced in the literature to test the degree of international financial market integration (Kearney & Lucey, 2004). The first is the International CAPM (Grauer, Litzenberger, & Stehle, 1976; Solnik, 1983), which is based on the assumption that financial markets are entirely integrated and beta[8] is the only source of risk. There have been some attempts to the use the International CAPM in single countries where the degree of stock market integration varies over time (Arouri, Nguyen, & Pukthuanthong, 2012; Bruner, Li, Kritzman, Myrgren, & Page, 2008), which use both local and global market portfolios as sources of risk.[9] For instance, Bruner et al. (2008) show that asset pricing models with domestic factors appear to contain more information because these markets exhibit a downward trend towards integration with the world market. Other studies propose an augmented version or test the International CAPM for partially integrated markets (Arouri et al., 2012; Blitz, Pang, & Van Vliet, 2013; Tai, 2007).

The second method arises from increases in the co-movement of international stock returns over time. Typically, researchers have focused on the correlation coefficient (Bekaert, 1995). Some later researchers have employed methods such as wavelet analysis (Graham, Kiviaho, & Nikkinen, 2012) or co-integration (Allen & Macdonald, 1995). While early studies found stability in the degree of correlation (Watson, 1980), further research has shown that the correlation structure may show instability over time (Junior & Franca, 2012; Longin & Solnik, 1995). A number of researchers suggest this is caused by macroeconomic linkages between countries (Arshanapalli & Doukas, 1993; Bracker, Docking, & Koch, 1999; Dickinson, 2000; Kizys & Pierdzioch, 2009; Neaime, 2012; Phylaktis & Ravazzolo, 2005; Pretorius, 2002; Vo & Daly, 2007). A potential weakness of these two methods is that they fail to account for the time-varying nature of the equity risk premium.

[8] Beta is the covariance between the asset and the world market returns divided by variance of world market returns.

[9] In testing the International CAPM we can use either country total market returns, or world market returns as a market risk premium. In a completely segmented market, the expected return is measured by local beta times the local market risk premium (given high volatility in market returns, the expected return should be high), whereas in an integrated market, the expected return is measured by world beta times the world market risk premium, this expected return is lower (Bekaert & Harvey, 2002).

Third, yet further research allows for the possibility of time variation in equity market integration. Bekaert and Harvey (1995) assume volatility in the market risk premium associated with time variation in market integration. The advanced model of Bekaert and Harvey (1995) and (Bekaert & Harvey, 2003) allows the degree of integration to vary over time, firstly by using a regime-switching model and secondly by incorporating time-varying betas in a multivariate setting.[10] Carrieri et al. (2007). Further studies show that the equity risk premium is time-varying and is determined by the volatility regime (Kim et al., 2004); therefore, modelling market integration without accounting for this phenomenon may provide misleading results.

This thesis considers these three quantitative methods in measuring market integration to derive a more efficient and practical technique for use in asset pricing and portfolio management. First, by accounting for the time-varying risk premium, the Markov-switching framework is incorporated into the International CAPM to test whether this can explain asset pricing behaviour in emerging markets. Second, by examining whether macroeconomic employed methods such effect cause time variations in the equity returns dynamic, which is potentially a better estimate of the International CAPM in an emerging market setting. Third, two proposed models employing the Markov-switching framework are used to optimize portfolio returns in a global investment setting.

1.5 Emerging Market Characteristics

Two salient characteristics of emerging market stock returns are higher market risk, as reflected by volatility (Bekaert & Harvey, 2014; Blitz et al., 2013; Umutlu et al., 2010), and time variation in the degree of co-movement between emerging market equity returns and developed market equity returns (Beine & Candelon, 2011; Bekaert & Harvey, 2014; Graham et al., 2012; Gupta & Donleavy, 2009; Junior & Franca, 2012).

While the volatility characteristics of emerging markets are notably different from those of developed markets, accurately measuring stock return volatility in emerging markets is difficult due in part to their inherent idiosyncrasies. For example, the previous literature documents distinct phases of volatility for emerging markets that are influenced by exchange rate regimes (Walid, Chaker, Masood, & Fry, 2011). Moreover, many of the factors that influence volatility change over time and from one economy to the next. One stream of research into influences on

[10] Other studies have characterized market integration using GARCH specification to account for time-varying risk premium (see e.g., Carrieri, Errunza, and Hogan (2007)).

volatility has concentrated on macroeconomic factors (Abugri, 2008) such as the consumer price index, industrial production (Corradi, Distaso, & Mele, 2013) and oil prices (Masih, Peters, & De Mello, 2011). Another strand of research focuses on the time-varying nature of asset returns to explain volatility behaviour (Campbell & Hentschel, 1992). Further complicating the volatility of stock returns in emerging markets is the susceptibility of these markets to crisis shocks (Calomiris, Love, & Pería, 2012). For example, Celık (2012) concludes that emerging markets are more influenced by contagion effects during a U.S. crisis than developed markets. Emerging markets are also subject to their own crises, such as the currency crisis in Turkey in 2001, the financial turmoil in Russia in 2014 and the economic crisis in Brazil in 2015. Additionally, emerging markets are more likely to experience sudden shocks due to regulatory changes (Cuadra, Sanchez, & Sapriza, 2010), exchange rate regimes (Falcetti & Tudela, 2006) and political crises (Boutchkova, Doshi, Durnev, & Molchanov, 2011; Chau, Deesomsak, & Wang, 2014).

From the viewpoint of international investors, the absolute risk of emerging markets is diversified away by the fact that they allocate only small shares of their portfolios to these markets; however, the degree of co-movement, as measured by the covariance or correlation between developed and emerging markets, is a more relevant as an ultimate risk factor. Since the beginning of the 1990s, when many emerging economies started liberalizing their capital markets, the diversification benefits of emerging markets have been recognised. Initially, emerging markets' correlation with the world index was relatively low, indicating potentially valuable diversification benefits. However, since then there has been a continuous increase in correlation, causing the benefits of diversification to diminish (Bekaert & Harvey, 2014). The primary reason for this increase in correlation is that some of the emerging markets began the liberalization process (defined as dropping all barriers to foreign investors participating in local markets) and that has led to increased correlation with the world market (Bekaert & Harvey, 2000; Henry, 2000).

Due to the non-normality in asset returns (Benson, Gray, Kalotay, & Qiu, 2008) and time-varying correlation among international markets, it is hard to identify an efficient model for portfolio selection. For example, in the Australian context, Gupta and Donleavy (2009) and Sukumaran, Gupta, and Jithendranathan (2015) applied an Asymmetric Dynamic Conditional Correlation GARCH model to account for these features and to examine the benefits of international diversification for Australian investors.[11] They find that, despite the increase in correlation among international markets, there are significant gains for the Australian investor from diversifying into emerging and frontier markets. To further demonstrate the potential benefits of international diversification for Australian investors, we will apply a state-dependent model as an alternative approach.

1.6 State-dependent Markov Model

This section reviews the two basic models, ARCH models and regime-switching models, that have been used extensively in modelling time-varying volatility. It also discusses the advantages of using state-dependent models to account for time-varying volatility in asset returns.

To deal with time-varying volatility in market returns, autoregressive conditional heteroskedasticity (ARCH) models have been introduced in the econometrics literature, starting with Engle (1982). This has been followed by a series of extensions and variations, including generalized ARCH (GARCH: Bollerslev (1986)). A newer class of multivariate models called dynamic conditional correlation (DCC-GARCH) models was proposed in Engle (2002). These have the flexibility of univariate GARCH models; however, financial time series generally display structural changes in their behaviour that are initially caused by structural changes and cannot be characterized by univariate or multivariate ARCH-type models (Cai, 1994; Hamilton & Susmel, 1994).

Further studies find that positive and negative shocks produce different impacts: volatility is more affected by negative shocks than by positive shocks. When this is so, ARCH and GARCH models are preferred as they account for volatility persistence (i.e. the fact that positive or negative shocks increase both current and future volatility: (Bekaert & Wu, 2000); however, these models assume that the variance process responds symmetrically to positive and negative shocks, which causes a substantial overestimation of the autoregressive parameters of the conditional variance (Hillebrand, 2005). Some studies have developed structural-time models to account for this asymmetric effect, for example Nelson (1991) Exponential GARCH model and Glosten, Jagannathan, and Runkle (1993) GJR-GARCH model.
The state-dependent Markov model (SDMM), introduced by Goldfeld and Quandt (1973) and Hamilton (1989), allows the data to be drawn from different distributions (states) where the

[11] Additionally, Hatherley and Alcock (2007) apply copula functions to show how asymmetric returns correlations alter portfolio performance with their application to Australian equities.

process is modelled by probabilities of switching between different states. Based on market return volatility, a degree of probability is assigned so that the process will either remain in the same state or transition to another state in the next period. The high volatility state is usually associated with extreme negative returns,[12] which cause non-normality in the distribution of market returns. The SDMM has the potential to distinguish between high and low volatility states to account for this salient feature in asset returns. In practice, the model tells the investor to switch to safer asset classes such as bonds when the market is in a high volatility state, which can provide further benefit in the construction of an international portfolio. Recognising the asymmetry effects noted above, this thesis incorporates an alternative approach by building on the SDMM, as that model responds asymmetrically to positive and negative shocks in market returns.

In modelling the risk premium, the state-dependent approach with a volatility-feedback[13] effect offers two advantages over other alternatives such as the broadly-employed ARCH-type specification (Kim et al., 2004). First, in a study of weekly equity returns, a state-dependent model with ARCH specifications has shown that ARCH dynamics may "die out"[14] (Hamilton & Susmel, 1994). By contrast, state-dependent changes tend to persist. Several other studies have successfully used a state-dependent specification to model monthly equity returns, *inter alia* (Abdymomunov, 2013; Augustyniak, 2014; Schaller & Norden, 1997). More recent studies (Augustyniak, 2014; Bensaïda, 2015; Christensen, Nielsen, & Zhu, 2015; Wilfling, 2009) combined two dynamic processes: ARCH specification and a Markov model. However, this combined approach only captures the high spikes in asset returns and tends to be useful only for high-frequency data, such as daily or hourly observations.

By capturing only substantial changes in market volatility (Hamilton & Susmel, 1994), a state-dependent model offers greater assurance than ARCH-type models that we are modelling the

[12] For example, Arouri, Estay, Rault, and Roubaud (2016) show that the extreme negative volatility state represents only 6 per cent of the US equity market observations. Krolzig (2013) also finds a similar pattern for industrial production in modelling business cycle.
[13] The volatility feedback effect states that large shocks, either positive or negative, cause high volatility, and that leads to another period of high volatility. If volatility is priced into asset returns, an expected increase in volatility requires an increase in the rate of returns on assets, which can only be achieved by a decrease in asset prices (Campbell & Hentschel, 1992; Pindyck, 1984; Wu, 2001).
[14] "Die out" is a term coined by Hamilton and Susmel (1994) and commonly used by researchers in this area to describe the process in which volatility effect reduces (by testing the presence of autoregressive conditional heteroskedasticity in residuals) when it is captured by Markov-switching models.

volatility feedback effect and not the leverage effect. The time-varying risk premium, or volatility feedback effect, states that an exogenous change in market volatility brings more return volatility as stock prices react to new information about future expected returns. If market volatility is persistent and directly corresponds to the equity premium, we should expect stock prices to move in the opposite way to market volatility level (Campbell & Hentschel, 1992). In contrast, the leverage effect hypothesis states that large shifts in asset prices change the debt-to-equity ratio of companies, swinging the risk profile and therefore leading to the higher future volatility of returns. In this case, the direction of causality is reversed relative to the volatility feedback, with the size of volatility changes being dependent on the size of price changes (Bekaert & Wu, 2000). Therefore, if the leverage effect was the leading cause of the adverse relation between volatility and realized returns, we should expect to see ARCH effects in the residuals from a model that only captures substantial changes in market volatility. Thus, state-dependent models are better suited to model volatility feedback.

Past research has identified some challenges in the analysis of time-varying volatility in market returns. First, given distinct distribution of market returns, it is unlikely that the typical ARCH models apply (Hamilton & Susmel, 1994). Thus, models that explicitly account for a fat-tailed distribution of market returns are preferable. Second, as emerging markets are gradually integrating with global markets, it is important for the model to allow for the importance of time-varying volatility in world markets. In fact, we are interested to find out what drives[15] the volatility behaviour in emerging markets and whether accounting for market phases (through a switching mechanism) can explain asset pricing behaviour. Additionally, we want to know whether, under higher levels of volatility, emerging economies demonstrate a higher degree of correlation with global capital markets.

1.7 Why Emerging Markets

Emerging markets research has continued to gain momentum, focussing on a variety of financial fields including asset pricing and portfolio theory, investments, risk measurement and management, and corporate governance (Kearney, 2012).[16] The considerable attention to emerging markets research is due to their fast-growing economies and the development of their financial

[15] Studies have used various factors as the key drivers of volatility behaviour in financial markets: local factors (e.g., liquidity and momentum) versus global factors (e.g., world market risk premium) as well as macroeconomic factors (e.g., exchange rate, interest rates).

[16] Emerging market research is still an ongoing research topic (Korinek, 2017; Miyajima, Mohanty, & Chan, 2015).

markets, which encourage scholars as well as portfolio managers to look at the investment opportunities of these markets from different angles. The liberalization wave has made emerging equity markets popular among international investors interested in diversifying their portfolios (Driessen & Laeven, 2007; Miyajima et al., 2015). This results in the development of different techniques. For example, Ghysels, Plazzi, and Valkanov (2016) have recently found that in a global portfolio setting, return asymmetry results in increasing the weight of emerging economies to about 30 per cent. More precisely, they find that the optimal portfolio is tilted towards markets that are less negatively skewed, mainly emerging markets.

Since the liberalization wave, the world equity market share of emerging equity markets has significantly increased relative to that of developed markets (Bekaert & Harvey, 1995, 2014; Blitz et al., 2013). To a large extent, this rapid growth has been driven by the issuance of new shares and to a smaller extent by higher market returns (Blitz et al., 2013). This rapid growth has not only held steady but is also expected to grow through risk aversion having increased significantly (Miyajima et al., 2015). This rapid growth is quite evident in the composition of MSCI Index, in which the share of emerging markets' capital has substantially increased from 4 per cent in 2001 to more than 11 per cent in 2016 (though there has been a significant fluctuation in emerging market weight during this time).[17]

In fact, the liberalization process has a dual effect on emerging markets investment; while it reduces investment barriers and capital flow restrictions, providing more investment opportunities, it causes a higher degree of correlation with world markets, thereby limiting diversification benefits. In a recent study, Bekaert and Harvey (2014) assume that the high correlation is the result of higher systematic risk and increases in the volatility[18] of world versus emerging markets returns. Additionally, the finance literature shows how national markets become more correlated during periods of market recession than in normal times (Ang & Bekaert, 2002a; Junior & Franca, 2012; Longin & Solnik, 2001). Accordingly, studies have shown that such asymmetric correlations caused by extreme shocks are statistically significant, leading to poor estimates of portfolio performance over periods of markets decline.

[17] MSCI uses free float-adjustment methodology. It defines as total shares outstanding excluding shares held by strategic investors such as governments, corporations, controlling shareholders, and management, and shares subject to foreign ownership restrictions. Using the World Bank data, emerging stock markets stand for more than 20% of total market capitalization.

[18] Bekaert and Harvey (2014) assume that the correlation between two markets can be specified as the product of the beta times the ratio of standard deviations, where the ratio of standard deviations is the historical standard deviation between world and emerging market returns.

In this thesis, we extend the existing literature by focusing on changes in emerging market equity returns and the correlation of emerging equity markets with the world capital market during different market phases. First, we analyse how the changes in correlation have been affected by global market phases and whether this can explain some of the asset pricing anomalies by incorporating a state-dependent International CAPM (SD International CAPM). The analysis of the changes in returns demonstrates how global equity markets influence each market and how this effect varies over time. Second, we test whether time-varying correlation of emerging markets during crises accrues substantial financial profit to international investors.

1.8 Research Questions

Market returns are a major determinant of both the cost of capital (Da, Guo, & Jagannathan, 2012) and asset allocation strategies (Ang & Bekaert, 2002a, 2004; Bae et al., 2014; Basak & Chabakauri, 2010; Guidolin & Timmermann, 2008). Indeed, a better understanding of returns behaviour will help to improve asset allocation decisions, leading to more effective portfolio diversification. This research aims to enhance the knowledge of returns behaviour in emerging economies and equity market co-movements with developed markets. Our analysis is based on a method in which the returns generating process is modelled as time-varying, characterised by market phases. This thesis looks at the applicability and suitability of state-dependent asset pricing models and how practitioners can implement this method when evaluating the performance of a portfolio. In particular, we aim to address four research questions.

1. Does accounting for market phases (i.e., time-varying volatility in the equity risk premium) better contribute to explaining the expected returns in emerging equity markets?
2. Does modelling market phases as determined by a macroeconomic variable (i.e. interest rate) in addition to time-varying volatility in the equity risk premium better explain the expected returns in emerging markets?
3. Can asset allocation strategies be improved by explicitly modelling market phases?
4. Can asset-allocation strategy be improved by allowing the interest rate (in addition to time-varying volatility in equity risk premium) to determine the market phases?

1.9 Research Contributions

The findings of this thesis contribute to knowledge of and research on asset pricing models and asset allocation strategy in three key ways.

First, this thesis extends the state-dependent asset pricing models to the emerging market setting. The findings show that an SDMM, when controlled for time-varying risk premia, outperforms the Conditional International CAPM models such as the Fama and French model and the GARCH model. More precisely, the International CAPM incorporating an SDMM to control for time-varying risk premia and using a macroeconomic factor to identify the market phases provides new insight into asset return behavior in emerging markets.

Second, two factors are employed to identify the transitions between states: one, volatility in the market risk premium (an endogenous variable known as constant transition probability), and two, an economic predictor (an exogenous variable known as time-varying transition probability). Using these two factors enables identification of the key global variables that drive volatility in emerging markets.

Third, the approach is applied in global portfolio settings, including both emerging and developed markets, and new evidence is found regarding the risk assessment of portfolio and asset allocation decisions with practical applications for fund managers. we find that emerging markets are characterized by different distributions of returns in different market phases relative to the world equity markets: a high variance state with lower expected returns and a low variance state with higher expected returns. This is consistent with the initial belief that the presence of two states and two optimal tangency portfolios is superior to a single unconditional optimal portfolio. we present evidence to show that investors can optimize (or improve) returns on their investments by diversifying their portfolio with emerging markets stocks.

1.10 Thesis Structure

The remainder of this thesis is structured as follows. Chapter 2 discusses the dynamics of emerging markets and the potential benefits open to international investors from diversification into these markets. Chapter 3 investigates an alternative estimation technique of conditional asset pricing models (SD International CAPM), first by accounting for time variations in betas relating to distinct volatility changes in equity premium, and second by studying the explanatory power of the model during different market phases in emerging market settings. Chapter 4 demonstrates the dynamic linkage between international equity market volatility and interest rates as a state predictor and explores whether these factors better explain asset pricing anomalies (using macroeconomic variables to identify the changes in equity returns behaviour). Chapter 5 explores how the developed models in previous studies are implemented in an asset allocation approach that provides for the formation of an optimal portfolio. Chapter 6 concludes the thesis, giving a summary of research contributions and a plan for further research.

Chapter 2 Emerging Markets Overview

2.1 Introduction

This chapter discusses the dynamics of emerging markets and the potential benefits open to international investors from diversification into these markets. In doing so, it focuses on the characteristics of emerging economies, and the features that distinguish them from developed economies.

There are two main reasons for equity investors to consider diversification into emerging economies: risk reduction through diversification and return enhancement. First, although the liberalization process has increased the level of correlation between emerging and developed markets, causing the benefit of diversification to diminish, these markets are still not fully integrated with the world capital market (Guesmi & Nguyen, 2011). Moreover, a recent study found the degree of correlation among emerging markets to be dependent on market phases (Christoffersen, Errunza, Jacobs, & Langlois, 2012a).[19]

Second, the higher returns that are expected to be available in emerging economies make these markets an attractive investment opportunity from the viewpoint of international investors (Bekaert & Harvey, 1995; Bodie, Drew, Basu, Kane, & Marcus, 2013). Even though it has been argued by many academic studies that these markets are more influenced by political (Boutchkova et al., 2011; Chau et al., 2014), economic and exchange rate risks (Falcetti & Tudela, 2006), they have the potential to yield substantial returns and are becoming more accessible as their underlying economies develop and open up. The Organization for Economic Co-operation and Development (OECD) has forecast significant economic growth for developing countries over the next 40 years (Johansson et al., 2012).

While emerging markets account for more than 30 per cent of the world Gross Domestic Product (GDP), they represent only 11 per cent of world equity markets (MSCI 2016). Their incomplete degree of correlation with the world capital market, along with their relatively small portion of world equity, provides potentially attractive investment opportunities (Bekaert & Harvey, 2014). Thus, a description of stock market volatility and returns in emerging markets is essential to the investigation of asset allocation strategy and decision-making on investment in these economies.

[19] Emerging markets offer further diversification benefit during market downturns.

The diversification benefits of emerging markets have been questioned for two reasons: their increased degree of correlation between market returns as a result of the liberalization wave (Turgutlu & Ucer, 2010), and their susceptibility to both global and local crises (Celık, 2012; Chiang et al., 2007). Similarly to developed markets (Ang & Bekaert, 2002a), a recent study found different degrees of correlation among emerging markets depending on market phases (Christoffersen et al., 2012a). The significant economic growth of and increasing access to these markets, along with changes in the degree of correlation, have motivated us to revisit the diversification benefits offered by phase effects in these markets, by adopting a model that explicitly accounts for changes in market phases.

The next section gives an overview of the characteristics of emerging markets, reviews the role of emerging markets in the global economy, and discusses the return benefit from investing in emerging markets.

2.2 Emerging Markets Classification System

While the term "emerging markets" is used widely, there is no universal agreement on the theoretical or practical definition of what an emerging market is (Kearney, 2012). As a result, the classification of emerging financial markets remains somewhat arbitrary and is reassessed differently by different international financial and economic institutions from time to time, using a range of categories and techniques.

Moreover, there is inconsistency in market classification. This inconsistency gives different total emerging market capitalization in different indices. For instance, the Financial Times Stock Exchange (FTSE) benchmark index[20] classifies South Korea as a developed market, whereas in the MSCI benchmark index it is listed as an emerging market. On the other hand, the World Bank uses the Atlas method to classify countries according to their national income. South Korea, Hungary, Poland, Greece and the Czech Republic are high-income economies

[20] FTSE applies the country classification process, classifying emerging markets into advanced and secondary markets and forming indices for large and small companies.

according to the World Bank, but their financial markets are classified as emerging markets by MSCI.[21]

MSCI uses free float-adjustment methodology. It defines as total shares outstanding excluding shares held by strategic investors such as governments, corporations, controlling shareholders, and management, and shares subject to foreign ownership restrictions. Using the World Bank data, emerging stock markets captures more than 20% of total market capitalization.

In this study, I select emerging markets based on the MSCI classification scheme. MSCI's emerging market indices include 23 countries in four geographic regions as follows: the Americas (Brazil, Chile, Colombia, Mexico and Peru), Asia Pacific (China, India, Indonesia, Malaysia, the Philippines, Taiwan, Thailand and South Korea), Europe (Greece, the Czech Republic, Hungary and Poland) and West Asia and Africa (Egypt, Qatar, Russia, South Africa, Turkey and the UAE).[22]

The criterion for MSCI classification is based on a country's economic development, market size and liquidity and market accessibility, or openness to foreign ownership rather than just economic indicators (as this is the case for the World Bank for example). MSCI also uses free float-adjustment methodology; it defines as being total shares outstanding excluding shares held by strategic investors such as governments, corporations, controlling shareholders, and management, and shares subject to foreign ownership restrictions. This ensures a reliable benchmark for international investors about the performance of these markets as reflected by others that used MSCI emerging market index: Graham et al. (2012), Hau, Massa, and Peress (2009) and Ané, Ureche-Rangau, Gambet, and Bouverot (2008).

2.3 The Role of Emerging Markets in Global Economy

In the early 2000s, the U.S., Japan and Germany combined represented 50 per cent of the world GDP, whereas China represented less than 5 per cent. By the end of 2015, the proportion for China grew to nearly 17 per cent while the combined weight of GDP for the U.S., Japan and Germany dropped to less than 40 per cent (Table 2.1). As the data of the World Bank suggests,

[21] The World Bank uses the Atlas method to classify the countries according to their Gross National Income (GNI). If a country's GNI per capita does not meet the World Bank's threshold for a high-income economy, then the country is classified as developing economy; hence, so is its financial market. Upper-middle-income economies are sometimes referred to as developing economies. Countries with GNI between USD 4,035 and USD 12,475 as of July 2015 are considered upper-middle-income, and those with GNI below that are said to be lower-middle-income. Recently the World Bank has removed this classification system.

[22] Taiwan and China are not listed as separate countries in World Development Indicator provided by the World Bank. However, Taiwan is classified by MSCI as a separate emerging market.

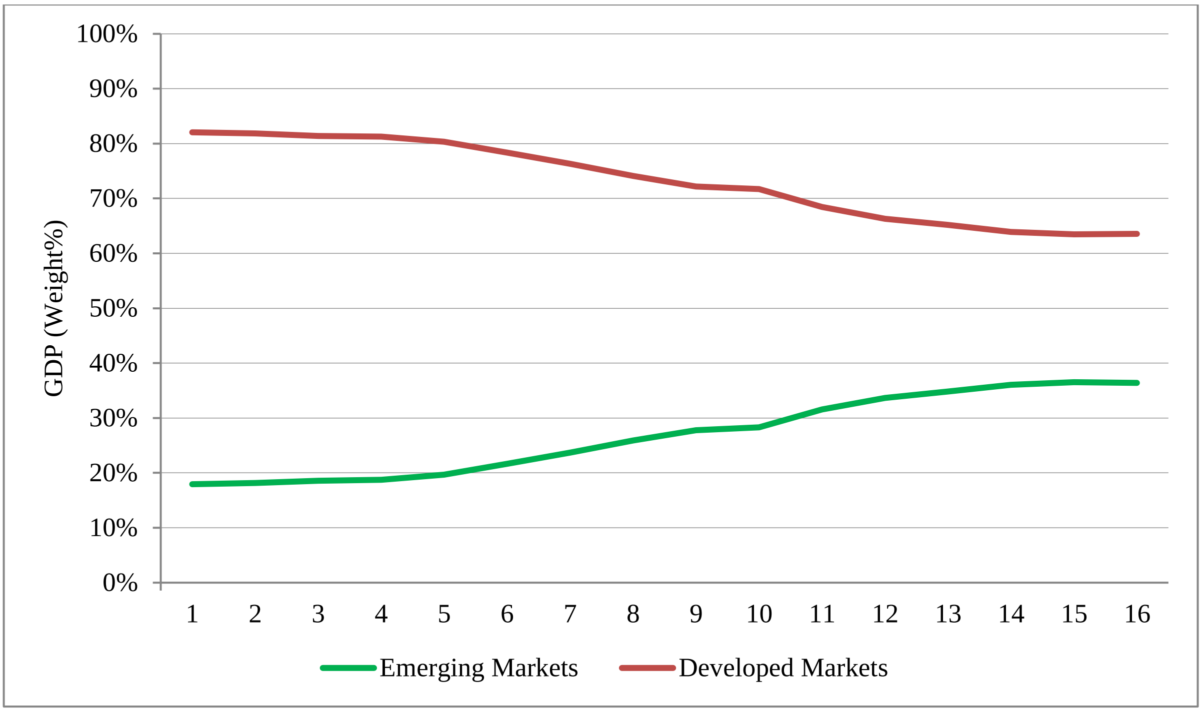
it is anticipated that emerging markets' proportion of the GDP will soon exceed that of developed economies (Figure2.1). In 2001, emerging markets' share of GDP made up about 18 per cent of the world GDP. At the same time, the market capitalization of emerging markets was as small as 4 per cent of the world market capitalization, as displayed in Figure2.2. By 2015, emerging markets made up about 36 per cent of the world GDP as well as 25 per cent of the world market capitalization.

The notable highlight is that while both market capitalization and the GDP weight of emerging markets have appeared to grow, they are still not at the same level (Bekaert & Harvey, 2014). In comparison, the U.S. represented 27 per cent of world GDP and about 41 per cent of the world market capitalization. Table 2.2 shows the top ten most underweight and overweight countries regarding GDP weights and MSCI market capitalizations. Out of the ten most underweight markets, seven are emerging markets, with China and India on the top of the board.

Table 2.1 Proportion of world GDP (current US$)

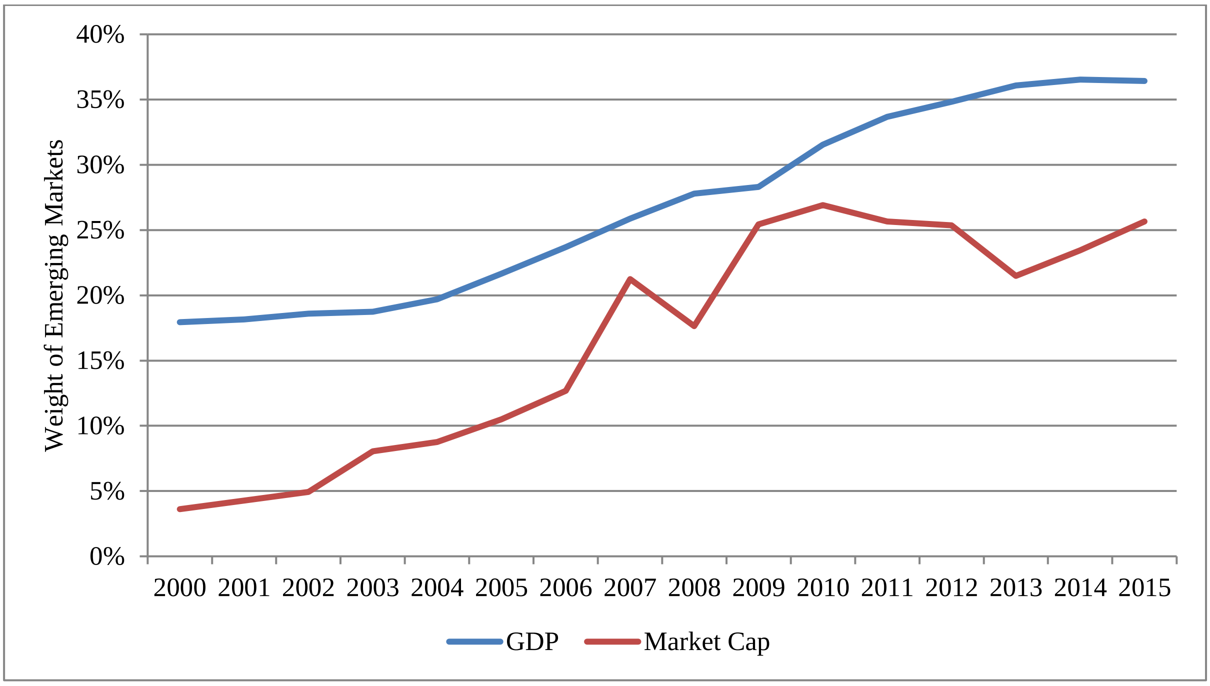
Rank	2001		2015	
	Country	GDP Weighted	Country	GDP Weighted
1	United States	34.36%	United States	27.18%
2	Japan	13.92%	**China**	16.59%
3	Germany	6.31%	Japan	6.60%
4	United Kingdom	5.22%	Germany	5.07%
5	France	4.47%	United Kingdom	4.31%
6	**China**	4.33%	France	3.64%
7	Italy	3.76%	**India**	3.16%
8	Canada	2.38%	Italy	2.74%
9	**Mexico**	2.34%	**Brazil**	2.67%
10	Spain	2.03%	Canada	2.34%

Source: The World Bank (2017b), annual GDP (current US$).



Source: The World Bank (2017b), annual GDP (current US$). Author's calculations.

Figure 2.1 Emerging and developed markets' share of GDP



Source: The World Bank (2017d), annual GDP (current US$) and annual market capitalization of listed domestic companies (current US$). Author's calculations.

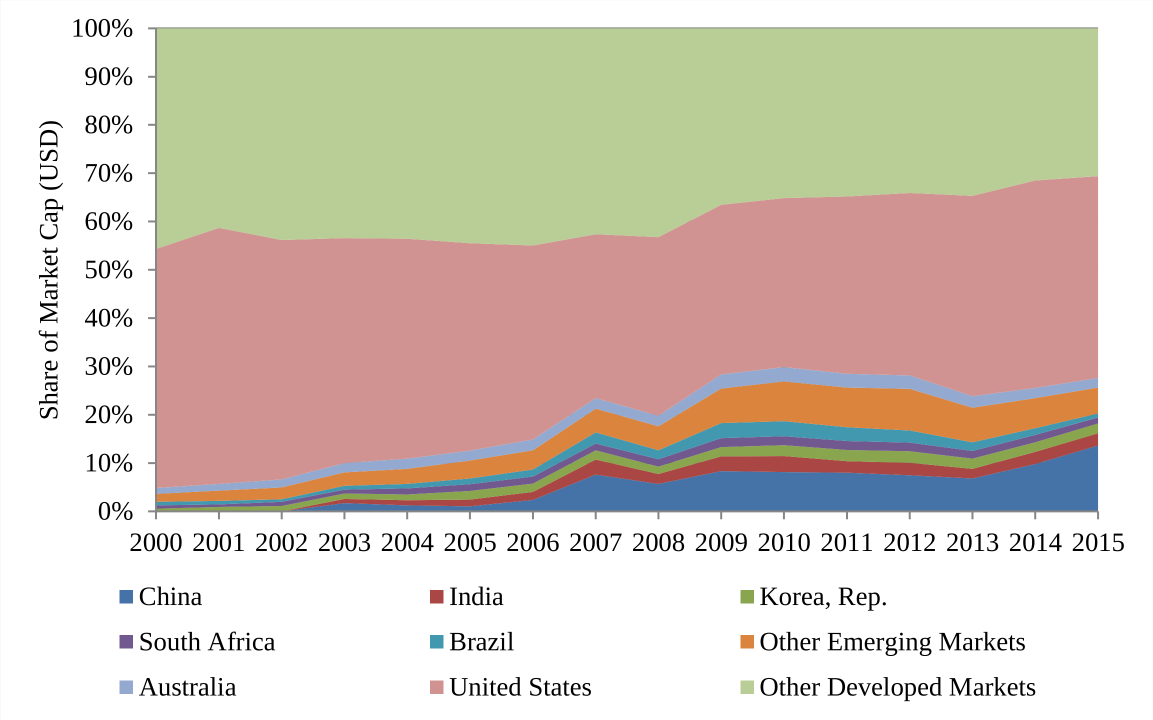
Figure 2.2 Share of market capitalization emerging and developed markets

Table 2.2 Top 10 underweight and overweight markets in MSCI GDP-weighted indices

	GDP Weighted Index	MSCI ACWI Index	Difference		GDP Weighted Index	MSCI ACWI Index	Difference
Underweight				Overweight			
China	16.59%	2.80%	13.79%	United States	27.18%	53.80%	-26.62%
India	3.16%	0.90%	2.26%	Switzerland	1.01%	2.80%	-1.79%
Germany	5.07%	3.00%	2.07%	United Kingdom	4.31%	5.90%	-1.59%
Italy	2.74%	0.70%	2.04%	Japan	6.60%	7.80%	-1.20%
Brazil	2.67%	0.80%	1.87%	Canada	2.34%	3.30%	-0.96%
Russian	2.01%	0.50%	1.51%	Hong Kong	0.47%	1.10%	-0.63%
Mexico	1.72%	0.40%	1.32%	Australia	2.02%	2.40%	-0.38%
Indonesia	1.30%	0.30%	1.00%	South Africa	0.47%	0.70%	-0.23%
Turkey	1.08%	0.10%	0.98%	Sweden	0.75%	0.90%	-0.15%
Spain	1.81%	1.00%	0.81%	Denmark	0.44%	0.50%	-0.06%

Source: Msci (2017a) and Msci (2017b). MSCI ACWI is a free float-adjusted market capitalization weighted equity index for both emerging and developed markets. Data as of December 2015.

Figure 2.3 depicts the growth of emerging markets' share of GDP capitalization over the last decade in comparison to the share of developed markets. Note that we use market capitalization provided by the World Bank, which consists of shares of listed domestic companies, including common and preferred companies, those without voting rights, and foreign companies, which are exclusively listed on an exchange. By contrast, most providers, such as FTSE and MSCI, do not account for all market capitalization. Instead their indices cover the free float-adjusted market capitalization in each country. Some companies' shares in some of the emerging economies may not be available for trading because they are government-owned. As a result, emerging markets have a lower ratio of free float than developed markets. However, the free float does not represent all of the underweighting in the emerging markets shown in Table 2.2. While the emerging market capital weight of free float is 10.55 per cent as of December 2015 according to the MSCI Index, the share of total market capitalization is 25 per cent according to the World Bank, which is far less than 36 per cent share of emerging markets' GDP; a significant growth in comparison to their capital weight in 2001.



Source: The World Bank (2017d), annual market capitalization of listed domestic companies (current US$), 2017. Author's calculations.

Figure 2.3 Share of market capitalization of emerging and developed markets

2.4 Review of Emerging Markets Performance

Due to the popularity of market capitalization benchmarks and the impact of home country bias,[23] emerging markets' weight is relatively less than their economic weight in international investment portfolios. To examine the diversification benefits of investment in emerging markets, in this section the risks and returns of both emerging and developed markets are compared. To maintain consistency and provide reliable comparisons throughout the rest of the empirical chapters, we utilize weekly observations of the MSCI indices for both emerging and developed markets from January 2001 to December 2015.

[23] "Home country bias" points to the fact that international investors allocate relatively small portions of their portfolios to international markets and that the portion allocated to emerging markets is smaller still.

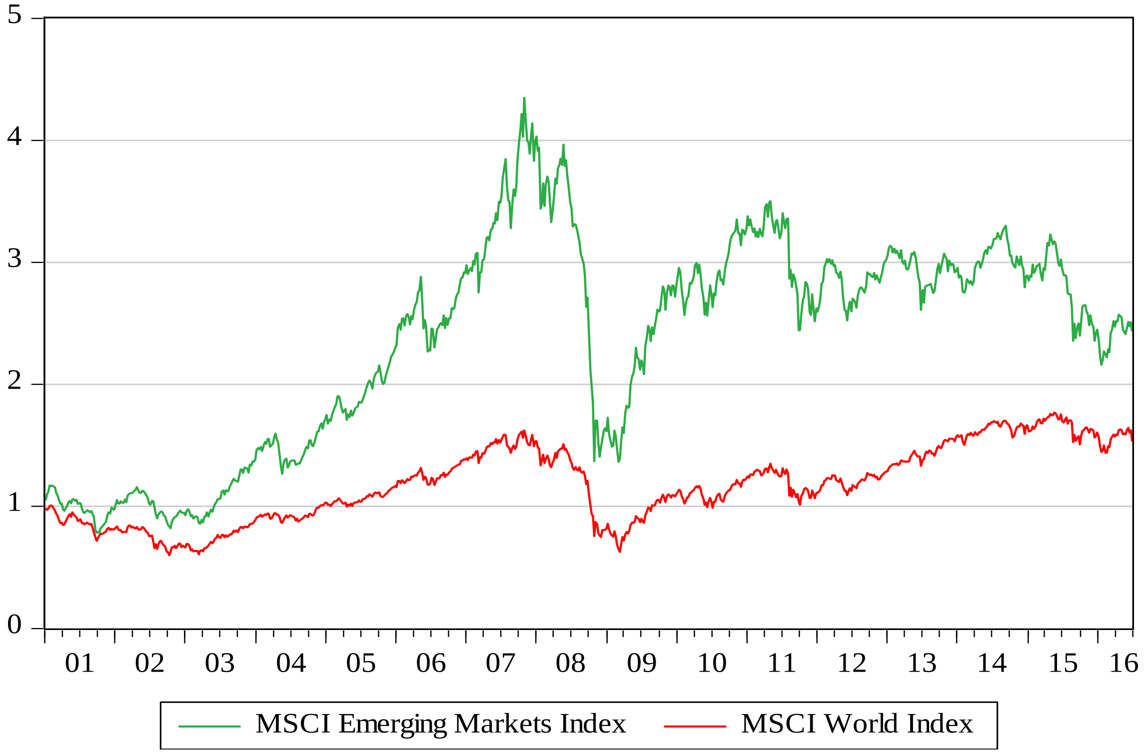


Figure 2.4 Cumulated returns of $1 invested in MSCI Emerging Markets and World Indices

This Figure illustrates cumulated weekly returns of $1 invested in MSCI Emerging Markets and World Index for period January 3, 2001 till June 29, 2016. Returns measured in excess of US Treasury bill rate. Source: Data collected from DataStream for MSCI Indices. Author's calculations.

Looking at the emerging market indices in Figure2.4, they outperformed developed markets before the Global Financial Crisis (GFC) of 2008–09, although the indices show higher volatility during that time. Both indices are fixed at $1 investment in early 2001. The emerging market index had moved up to approximately $4.50 before the GFC, while the world index had moved up to only $1.50. The emerging market index has remained at around the same level since then, but with higher volatility.

Table 2.3 Panel A provides a comparative performance of total returns for both emerging and developed markets. Looking at the period before 2008, the average annualized excess returns for developed markets was -1.26 per cent in USD, and 9.48 per cent for the emerging market index ($r_i \times 52 \times 100$); however, the volatility as measured by the annualized standard deviation was 18.82 per cent for the developed markets index and 26.16 per cent for the emerging markets index ($SD \times \sqrt{52} \times 100$). Even though volatility is higher, the Sharpe ratio for emerging markets is higher still. The benefit of emerging market investment is further highlighted during

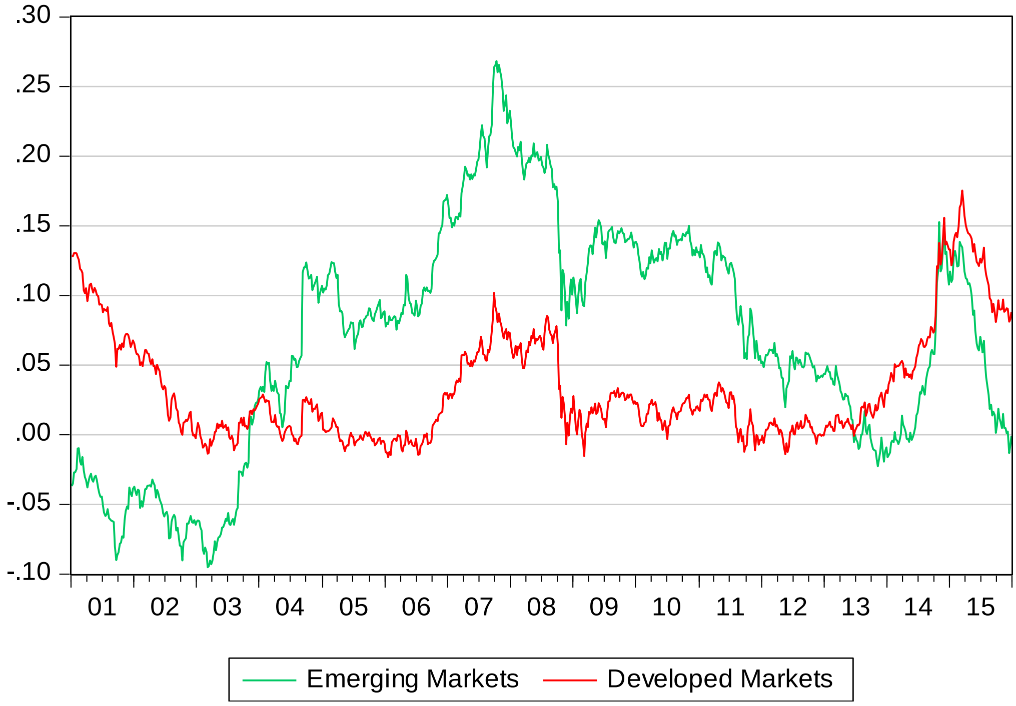
2008–09 as the financial crisis significantly undermined the performance of the developed markets. Despite being affected severely by the crisis as well, the share of market capitalization of some large emerging markets, such as Brazil, China, India and South Africa, increased over the last decade (Figure2.3).

Table 2.3 Comparative performance of total return for developed and emerging markets

Panel A.	MSCI Developed Markets	MSCI Emerging Markets
January 2001 to December 2008		
Average Annualized Excess Return (%)	-1.26%	9.48%
Annualized Standard Deviation (%)	18.82%	26.16%
Sharpe Ratio	-0.1437	0.3069
January 2009 to December 2015		
Average Annualized Excess Return (%)	11.85%	8.42%
Annualized Standard Deviation (%)	18.84%	22.33%
Sharpe Ratio	0.5519	0.3120
Panel B. Downside and Tail Risk		
Average Weekly Total Return	0.09%	0.17%
Standard Deviation	2.61%	3.39%
Skewness	-0.61	-0.58
Kurtosis	5.45	8.67
VaR (95%)	-3.88	-4.94
VaR (99%)	-7.71	-9.41
Average Negative Returns	-1.02	-1.33
Average Positive Returns	0.93	1.21
Panel C. Alternative Measures of Diversification		
Average Returns when DM Return is Negative	-1.0171	-1.0600
Average Returns when DM Return is Positive	0.9278	1.0387

Panel A shows the average annualized weekly returns in excess of US T-bill, annualized standard deviation and Sharpe ratio. In Panel B, average weekly total returns and standard deviation of weekly returns are shown. They are not annualized. Value-at-Risk is the realized weekly percentage loss at 95 per cent and 99 per cent confidence level. The skewness and kurtosis are measured in the standard way. In Panel C, average negative and positive returns are simple averages conditional on the returns being negative or positive respectively. Source: DataStream, MSCI indices.

A. Average weekly annualized excess returns (5-year trailing)



B. Average weekly annualized standard deviation (5-year trailing)

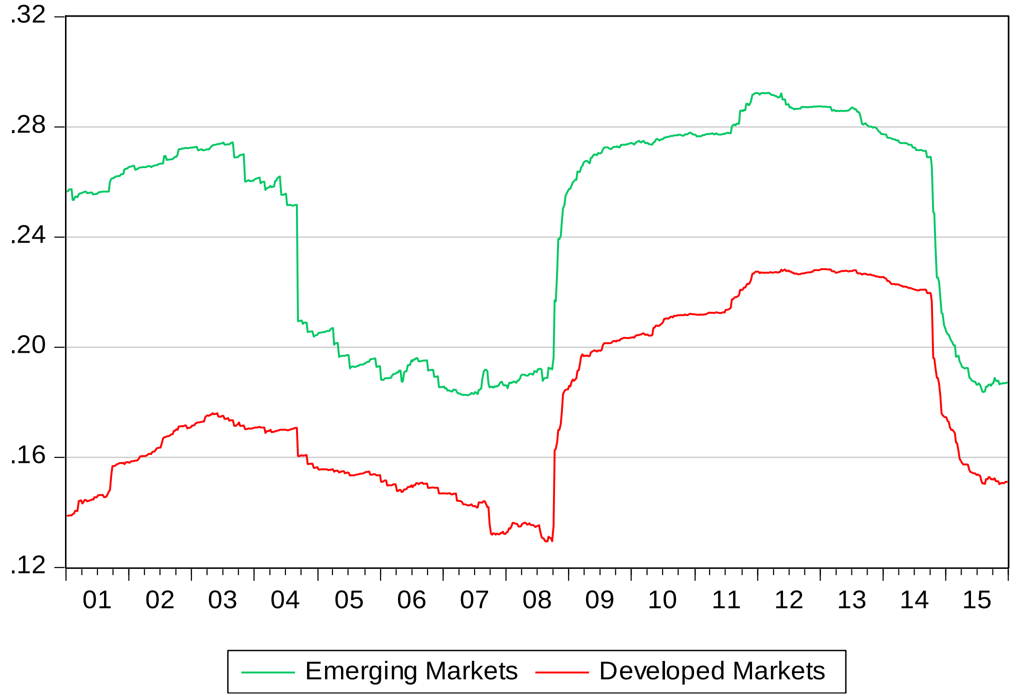


Figure 2.5 Annualized 5-year excess returns and standard deviation

Source: DataStream, MSCI indices. Author's calculations.

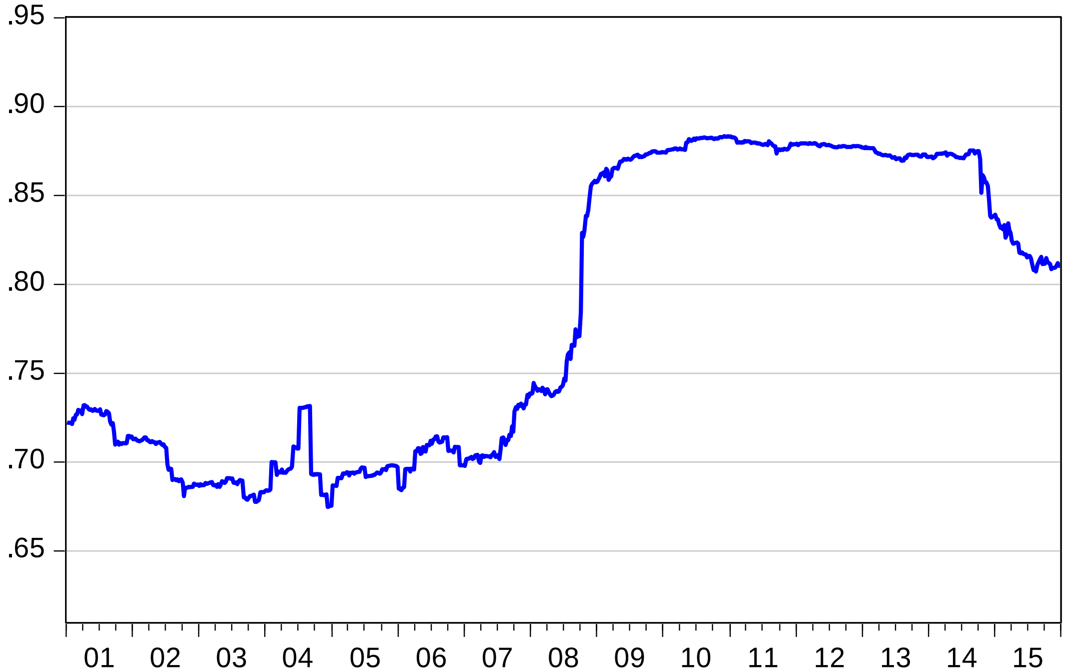
The rolling five-year excess returns in Figure2.5 Panel A shows a considerable run-up in emerging market performance, and relatively fewer negative returns are seen for emerging markets over the last 10 years. The relatively high volatility of the emerging market index is because of the substantial weight of the low volatility US market in the developed market index as well as the diversification effect of investing in all of the world's equity (Bekaert & Harvey, 2014). In addition to this, looking at each emerging market separately, the volatility is even higher than the volatility of the emerging market index (See Table 3.1 in Chapter 3). The rolling five-year standard deviations in Figure2.5 Panel B illustrate that the volatility of the emerging market index has surged between in the 18 per cent to 29 per cent, but it has recently been closer to the lower end of the range.

It is also evident that during some periods when the developed markets performed relatively weakly, so did the emerging markets, but by a higher magnitude due to their high volatility. However, there are times when the return gain appreciation of emerging markets could compensate for their loss during market downturn. Thus, the risks of emerging market investment can to some extent be offset and they can provide a diversification benefit regarding risk-return relationship into global equity portfolio.

In addition to simple standard deviation as a measure of risk, we also assess downside risk.[24] Table 2.3 Panel B shows that the non-normality in the emerging market index is notably different from the non-normality in the developed market index, exhibiting higher kurtosis at 8.67. The asset returns are not normally distributed, and this is the case for emerging market returns as well (Bekaert et al., 1998). The Value-at-Risk (VaR),[25] as a measure of downside risk, is -9.41 per cent for emerging market returns compared to -7.71 per cent for developed markets which is mainly a result of the higher variance of emerging market returns. Considering all the risk characteristics of emerging markets, the downside risk is more pronounced in these markets.

[24] Downside risk is the financial risk associated with loss on an investment.
[25] Value-at-Risk measures the risk of loss on an investment with a given probability.

A. Emerging markets correlation with developed markets (5-year trailing)



B. Emerging markets beta (5-year trailing)

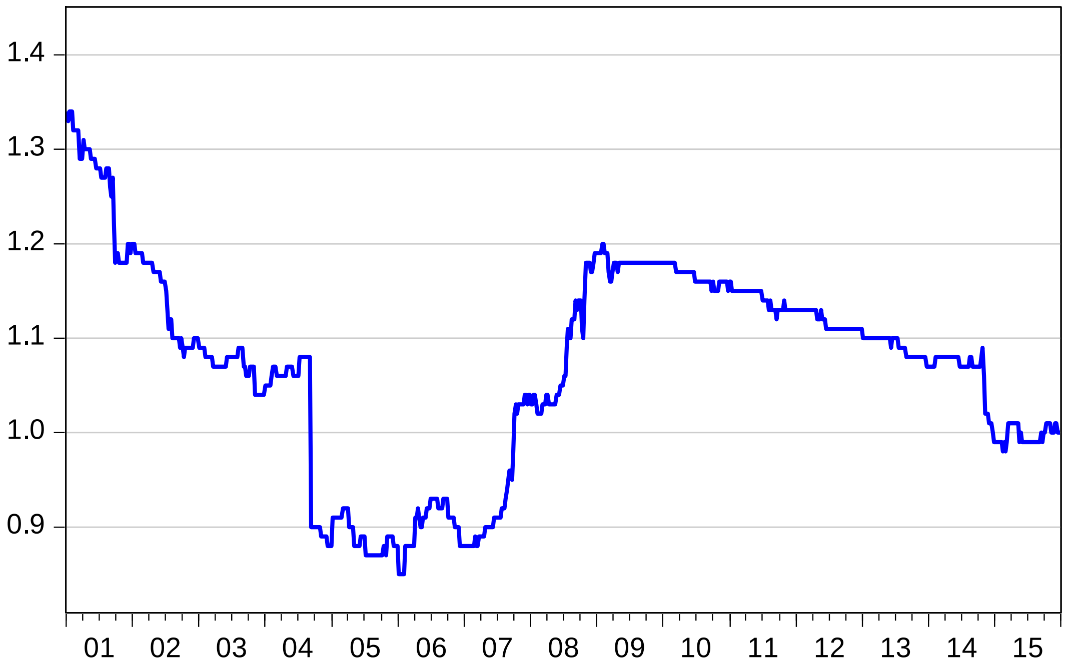


Figure 2.6 Emerging markets rolling correlation and beta

Figure 2.6 depicts emerging markets rolling correlation (Panel A) and rolling beta (Panel B) with developed markets. Source: DataStream, MSCI indices. Author's calculations.

2.5 Market Integration

From the investment viewpoint, the absolute risk[26] of emerging market returns is diversified away by the fact that international investors in developed markets allocate only a small share of their portfolios into emerging markets. However, the correlation between developed markets and emerging markets is a more relevant factor to consider as an ultimate risk factor. In the early 1990s, when investment in emerging markets became more feasible for international investors, their diversification benefits attracted greater attention. The correlation of the emerging market index with the world index was about 0.40 at that time, pointing to noticeable diversification benefits (Bekaert & Harvey, 2014). However, the correlation reached over 0.90 in 2008–2009.

As Figure 2.6 Panel A shows five-year rolling window correlation. The results show that more recently the correlation has been fluctuating between 0.81 to 0.88. The primary reason for this increase in correlation is that some of the emerging markets began the liberalization process in the early 1990s, and that increased their correlation with the world markets (Bekaert & Harvey, 2000; Henry, 2000). The continuous increase in correlation has remained somewhat steady, causing the benefits of diversification to diminish. To some extent the higher degree of correlation is the result of higher systematic risk in relation to the world market, as illustrated in Figure 2.6 Panel B. In addition, the heightened correlation can be partly explained by a general increase in the world versus emerging market volatility, as it is about 6 per cent higher on average (Figure2.5 Panel B). Betas appear to vary in a band between 0.85 and 1.35, making the assets in emerging markets riskier than those in developed markets; hence, high returns are expected. However, the high beta alone is not enough to justify the higher returns gained by emerging markets since the early 2000s. As indicated in Table 2.3 Panel B, the further returns of emerging markets earned over and above the return of developed markets was about 4 per cent on average per year since 2001, and this return was higher before 2008.

There are some interesting facts behind the high average correlation. Table 2.3 Panel C divides the positive and negative returns. Emerging markets earn a similar return to developed markets when developed markets generate negative returns. However, emerging markets earn higher

[26] Absolute Risk defines as the ratio of risk associated with investing in emerging markets compare to the risk of investing in developed markets. From the viewpoint of international investors (here the US investors) the investment portfolio in emerging markets is relatively small compared to investment portfolio in developed markets. Therefore, the risk (in this case the high risk of investment in emerging markets during bear market) associated with investment in emerging markets would diversify away by the fact that international investors have a relatively small proportion of their investment in emerging markets (Bekaert & Harvey, 2014).

returns than developed markets when developed markets generate positive returns. Put differently, the downside risk of emerging markets is not as high as is suggested by beta estimation alone. On the other hand, the performance of emerging markets is more favourable when developed market returns are positive (Table 2.3 Panel C).

In summary, the high correlation between developed and emerging markets is a result of higher systematic risk, which is due to a general increase in market volatility, consistent with the findings of (Bekaert & Harvey, 2014). However, when we separate out the positive and negative returns, the downside risk of emerging markets is not as high as indicated by beta estimates (Table 2.3 Panel C). In fact, emerging markets perform relatively similarly to developed markets in period of market turbulence but outperform developed markets during normal times.

Note that these outcomes are based on averages calculated over a specific time, and changes in economic and political factors could alter these estimates along with correlation. Of course, the results in this sample may be closely related to the recent financial crisis. The historical pattern also only serves as an indication of future return behaviour. This finding, however, is consistent with previous studies that characterized nonlinear dependence and asymmetry in emerging market returns (Bekaert & Harvey, 2014; Christoffersen, Errunza, Jacobs, & Langlois, 2012b).

2.6 Economic Diversity

The emerging markets data in this chapter consists of the equity markets included in the MSCI Emerging Market indices. These countries represent a total population of more than 4.07 billion people as of December 2015, accounting for more than half of the world population (Table 2.4). Since 2001, there has been an average of 15 per cent population growth and hence potential market participants in world business, but that population growth varies significantly across countries. For instance, while the UAE and Qatar have exhibited considerable population growth (the population has doubled from 2001 to 2015), most of the countries in Europe and West Asia (e.g., Greece, Hungary, Poland and Russia) show negative population growth.

Table 2.4 shows other features of the emerging markets. We observe an average per capita GDP for emerging markets, as a proxy for average income, of USD 13,811 (USD 6307) at the end of 2015 (2001). The average income for emerging markets has more than doubled since 2001, whereas the USA's income has had a slower growth of 51 per cent over the same time interval. Overall, 80 per cent of the emerging economies included in the sample set have recorded higher GDP per capita than the USA between 2001 and 2015, suggesting potential economic growth in these countries. However, average inflation is recorded at the higher rate for emerging economies compared to the USA. The data also shows that Russia, Turkey and Egypt experienced the highest average price increases among emerging economies during the stated period.

2.7 Market Size and Activity

Stock market capitalization is one of the key indicators of financial development, in that larger market size suggests a more developed institutional framework. In 2001, the total market capitalization of emerging markets was USD 1.1 trillion, while the total market capitalization of developed markets was USD 25.2 trillion (The World Bank, 2017d). By the end of 2015, the total market capitalization of emerging markets has reached USD 15.4 trillion, with China accounting for USD 8.2 trillion, India for USD 1.5 trillion and South Korea for USD 1.2 trillion. At the same time, the total developed market capitalization was USD 44.6 trillion. Figure2.2 depicts the composition of each market across the world from 2001 to 2015. Together the emerging markets represent 25 per cent of the world market capitalization. China represents more than half of the emerging market capitalization, followed by India, South Korea and South Africa. Although the USA is still the largest market, its market capitalization shrank from 49.5 per cent in 2001 to 41.7 per cent in 2015.

Regarding GDP as an indicator for economic size, emerging economies currently include 8 of the 20 largest economies across the world.[27] The total value of listed companies in emerging economies as the percentage of GDP,[28] a proxy for market size, has increased from 45 per cent in 2001 to 61 per cent in 2015 (Table 2.4). Indonesia, the Philippines, Thailand and India recorded the highest ratio of stock market capitalization to rates of GDP growth between 2001 and 2015. In contrast, the ratio was negative for Brazil, Greece, Hungary and Egypt.

[27] According to the International Monetary Fund world outlook report, the twenty largest economies at the end of 2016 were, in order of size, the USA, China, Japan, Germany, the UK, France, India, Italy, Brazil, Canada, Korea, Russia, Australia, Spain, Mexico, Indonesia, Netherland, Turkey, Switzerland, and Saudi Arabia.

[28] Market capitalization of listed companies (% of GDP) (See Appendix E, Table E1 for variable definitions).

Table 2.4 Characteristics of emerging markets

Country	Population (millions)		GDP per capita $		Inflation (2005=100)		Market capitalization of listed companies (% of GDP)		Stock traded, total value (% GDP)		Export of goods and services (% of GDP)	
	2001	2015	2001	2015	2001	2015	2001	2015	2001	2015	2001	2015
Brazil	178	208	3135	8539	6.84	9.03	33.29	27.64	11.53	23.66	12.37	13.04
Chile	15	18	4710	13416	3.57	4.35	77.84	79.05	5.63	8.17	30.87	29.98
China	1272	1371	1053	8028	0.72	1.44	-	74.38	34.55	357.26	20.84	22.09
Colombia	41	48	2396	6056	7.97	5.01	-	29.43	0.80	3.97	15.39	14.71
Czech Republic	10	11	6595	17548	4.71	0.34	12.10	-	5.12	-	49.14	82.96
Egypt, Arab Rep.	70	92	1403	3615	2.27	10.36	-	16.69	-	4.46	17.48	13.21
Greece	11	11	12538	18002	3.37	-1.74	62.23	21.60	27.26	9.21	22.79	31.92
Hungary	10	10	5271	12364	9.16	-0.07	-	14.53	-	6.11	64.89	90.73
India	1072	1311	461	1598	3.68	5.87	-	72.36	30.75	36.84	12.34	19.94
Indonesia	214	258	748	3346	11.50	6.36	14.33	40.99	6.01	8.71	39.03	21.09
Korea, Rep.	47	51	11256	27222	4.07	0.71	43.88	89.36	70.16	133.81	32.73	45.90
Malaysia	24	30	3879	9768	1.42	2.10	128.23	129.26	22.67	37.63	110.40	70.90
Mexico	104	127	6952	9005	6.36	2.72	17.42	35.17	7.33	9.06	23.64	35.36
Peru	26	31	1981	6027	1.98	3.56	18.82	29.91	1.41	0.77	16.60	21.30
Philippines	80	101	958	2904	5.35	1.43	27.86	81.66	3.95	13.14	46.03	28.19
Poland	38	38	4981	12555	5.49	-0.99	13.66	28.88	5.34	11.03	27.23	49.55
Qatar	1	2	28577	73653	1.47	1.88	-	86.59	-	14.67	65.89	56.06
Russian Federation	146	144	2100	9093	21.46	15.53	-	29.54	9.20	8.81	36.89	29.53
South Africa	45	55	2706	5724	5.70	4.59	121.36	233.95	29.10	74.38	29.37	30.72
Thailand	63	68	1897	5815	1.63	-0.90	29.88	88.27	25.81	68.66	63.25	69.06
Turkey	64	79	3054	9126	54.40	7.67	24.69	26.31	33.51	48.71	27.44	27.96
United Arab Emirates	3	9	32106	40439	-	-	-	52.90	-	15.55	49.16	97.36
United States	285	321	37274	56116	2.83	0.12	131.65	138.98	196.61	229.52	9.67	12.55

See Appendix E for variable definition (The World Bank, 2017a, 2017b, 2017c, 2017d, 2017e, 2017f)

Stock market total value traded as a fraction of GDP gives a complementary view by showing that market size is comparable with liquidity within these markets (Table 2.4). Average trading in emerging markets has increased from 17 per cent in 2001 to more than double this, 42 per cent, in 2015 implying a better liquidity level in their equity markets. The best progress regarding liquidity was recorded for Chinese and Korean markets and the lowest was recorded for Peru, Greece and Hungary during the same period. Although the USA market achieved higher liquidity between 2001 and 2015, the liquidity improved far less than the average liquidity for emerging markets.

2.8 Market Efficiency

Financial market efficiency is one of the key indicators used to distinguish between emerging and developed markets. The first concern in market efficiency arises from differences in national language and culture, which may convey asymmetric information to international shareholders. According to Young, Peng, Ahlstrom, Bruton, and Jiang (2008), publicly listed companies in emerging markets do not disclose consistent and sufficient information on their business activities and their prospects. The lack of updated news can reduce investors' confidence and may make the market riskier for investment; international investors may incur extra costs, such as information interpretation. It is fair to say that the fast rate of progress of foreign investment has imposed more pressure on these markets to provide more information disclosure and transparency, in line with developed markets (Solnik & Mcleavey, 2009).

The second concern regarding market efficiency arises from price manipulation and insider trading by domestic investors. Emerging markets have shown relatively ineffective corporate governance; studies have shown that majority shareholders, as controlling owners, can derive benefit from their controlling interest to the disadvantage of minority shareholders (Kato & Long, 2006; Klapper & Love, 2004). In many cases, foreign investment restrictions mean that international investors can only be minority shareholders. As a result, they have to accept a disproportionate share of the investment risk, giving an advantage to local traders engaging in price manipulation and insider trading (Young et al., 2008).

2.9 Capital Flow Restriction, Market Regulation and Accessibility of Emerging Markets

Capital flow restriction and market regulation are essential indicators that distinguish emerging markets from developed markets (Beine & Candelon, 2011; Umutlu et al., 2010). The market liberalization process[29] began in the 1990s in some emerging economies, and many of them are still in the process of development.

The surge of capital market liberalization makes emerging markets more open to global investors and is characterized by relaxed government restrictions and improved market legislation and surveillance activities. These factors contribute to the economic development of these markets; however, regulations in some emerging markets still restrict free market entry and exit and limit the amount of foreign investment in local firms. For instance, China's state-owned enterprises put restrictions on foreign ownership and the free float share of ownership is limited, while the government is the primary owner of these companies. In India, caps on foreign direct investment and difficulties in land acquisition for foreign investors, which prevent them from establishing factories in their preferred locations, make that market unattractive. As a result, data providers such as FTSE and MSCI have formed "investable indices" to reflect the investable portion of equity for foreign investors. In constructing global equity indices, foreign ownership constraints and free float influence the emerging market index constituents (Solnik & Mcleavey, 2009). That said, during the process of liberalization, emerging markets become more accessible and they do provide diversification benefits that are achievable for international investors.

The growing market liberalization process has led to more global market integration among financial markets, which in turn has influenced cross-border investment activity and may make investing in emerging markets less attractive. However, Li, Sarkar, and Wang (2003) find that integration of world equity markets does not reduce the diversification benefits of investing in emerging markets. In fact, the market liberalization process in emerging markets, along with integration with the world markets, brings more opportunities for international investors to pursue the diversification benefits of emerging markets. Given the process of liberalization, emerging markets become more accessible and they provide diversification benefits that are achievable for foreign investors. These improvements have increased confidence among global investors and reduced uncertainty due to policy changes (such as exchange rate, capital control and closing the financial markets) by creating the possibility of substantially lower returns and higher risk.

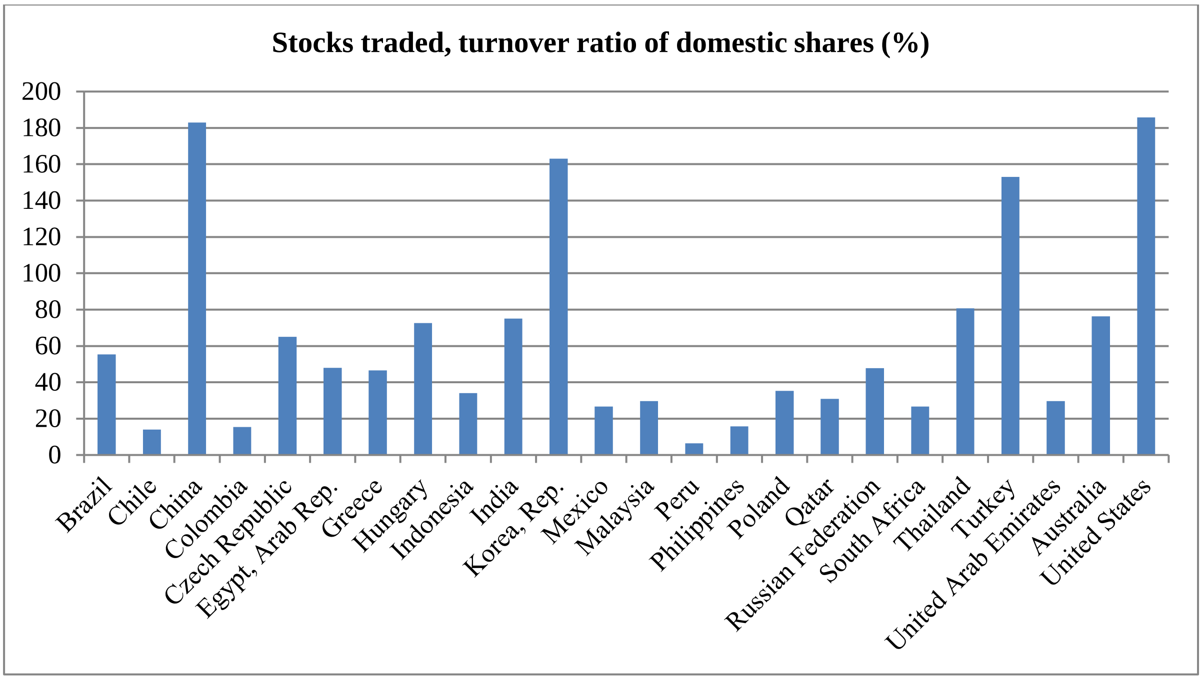
[29] The market liberalization process is defined as the lessening of government regulations and restrictions in the market to encourage capital movement and currency exchange.

2.10 Barriers to Investment in Emerging Markets

Factors that prevent the development of financial markets are considered in the literature. Currency risk is an essential factor that influences the benefit of emerging market investments (Bailey & Chung, 1995; Domowitz, Glen, & Madhavan, 1998). Generally, developed markets display a negative correlation with the value of their currency (Harvey, 1995); when the value of the local currency depreciates, the financial market within that country appreciates in value due to the improvement in international competitiveness of local firms. However, the situation in emerging markets is different; there is a positive correlation between market returns and the value of the currency in emerging markets. This positive correlation is because both the financial markets and the currency are influenced by the state of the economy, and in periods of market turbulence, both depreciate significantly (Solnik & Mcleavey, 2009). Consequently, investors may experience further loss from currency risk. To offset this devaluation effect and to have a consistent comparison between the equity markets in this study, all of the market indices are selected from MSCI funds and denominated in USD.

Transaction costs and short-sale constraints can keep investors out of emerging markets (De Roon, Nijman, & Werker, 2001). The transaction costs in many international markets can be higher than those in domestic markets, although it is difficult to estimate the exact transaction costs (Solnik & Mcleavey, 2009). First, there is wide variation in commission costs and these vary in the ways they are charged (for instance, fixed or variable commission or implicit buy-sell spreads,). Second is an expected price impact cost, since there is lack of liquidity in emerging markets (Lesmond, 2005).

For example, a large buy order may significantly increase prices. In those emerging markets where trading volumes are thin, institutional investors may be reluctant to invest because these markets are relatively less liquid. Unfavourable prices are expected and can make holding costs increase if buy and sell requests are not taking place, resulting in less liquidity. Thus, there could be a dramatic difference between informed indexes and actual portfolio returns (Lesmond, 2005). Figure2.7 provides the average yearly turnover ratio as an indicator of liquidity within equity markets. Among the selected emerging markets, China, South Korea and Turkey exhibit the highest liquidity.



This Figuredepicts the average yearly turnover ratio of domestic shares for selected market from 2001 till 2015 . Source: The World Bank (2017g).

Figure 2.7 The average yearly turnover ratio of domestic shares

Outside the scope of the analysis in this study, but worth mentioning here, is political risk.[30] Also outside this study's scope are risks arising from the prevalence of black money(known as the cash economy in financial literature), speculative investment and market predation, all of which could affect the market development process (De Brouwer, 2001). However, in real world practice, these factors have indirectly affected the portfolio selection by imposing constraints on asset allocation program, when investment managers apply the "prudent man rule".[31]

Based on the above discussion, it is of course expected that these barriers may affect investment flow into emerging markets and pose additional risk in a diversified portfolio. With regard to ongoing economic development and progressing market liberalization, emerging markets are

[30] The term political risk has had various meanings, but commonly refers to the political decisions, economic actions and events (e.g., civil war and terrorism) faced by investors, corporations and governments, which significantly affect the profitability of business sectors (Sottilotta, 2013). A leading organization in this field is the Political Risk Service Group, which provides information on country and political risks. Investors can evaluate the impact of country and political risk on multinational business operations and on the major asset classes.

[31] The "prudent man rule" claims to protect investors by allowing them to seek damages from investment managers who have fiduciary responsibility but fail to invest in their best interest. This principle may influence investment managers to behave conservatively in order to avoid losses on imprudent investments and to protect themselves from liability by tilting their portfolios toward high-quality, low--risk asset selections that are easy to defend in court (Chen, Yao, & Yu, 2007; Del Guercio, 1996).

encouraging more capital inflow to improve their financial condition. Given the progressive convergence of emerging economies with the developed world, fund managers are getting more access into emerging economies which offer more diversification benefits.

2.11 Conclusion

The world's market capitalization has experienced substantial growth and expansion, and emerging economies have been the main sources of capital growth. To a large extent, this has been driven by strong economic growth and the development of financial markets within these countries. Market capitalization weights are based on the amount of free float, not total market capitalization. If total market capitalization is taken into account, emerging markets represent about 25 per cent of world equity capitalization.

The high correlation between developed and emerging markets is a result of higher systematic risk, which is due to general increases in market volatility; however, when we separate out positive and negative returns, the downside risk of emerging markets is not as high as indicated by beta estimates. In fact, emerging markets perform similarly to developed markets during periods of market turbulence but outperform developed markets during normal times. This time-varying nature of returns makes emerging markets high return but risky investments.

The switching behaviour of emerging markets presented in this section highlights the primary objective of this study: to implement a more advanced technique for return estimation in emerging markets in order to bring further diversification benefits into international portfolio investment and risk management.

Chapter 3 The State-dependent International CAPM and Asset Returns: An Empirical Investigation of Emerging Equity Markets

3.1 Introduction

Emerging markets are distinct as clearly explained in Chapter 2 of the thesis. The research in the thesis makes a significant contribution to the research agenda for emerging markets outlined by Kearney (2012) around the risk adjusted returns and risk premia agenda in terms of the application of state dependant asset pricing models (Chapter 3 and 4) and the implications for asset allocation (Chapter 5).

The CAPM of Sharpe (1964), Lintner (1965) and Mossin (1966) has been prominent in finance and is used for asset pricing (Lewellen & Nagel, 2006), estimating the cost of capital (Da et al., 2012), evaluating stock price performance (Jawadi, Jawadi, & Louhichi, 2014) and measuring the extent to which financial markets are integrated (Bruner et al., 2008). The CAPM states that an asset's expected return has a positive linear relationship with the asset's systematic risk, where that risk is measured by CAPM beta.

One extension of the CAPM is an International version of CAPM, extending CAPM to take world equity markets into account. Several studies have effectively employed the International CAPM; for instance, Solnik (1974)[32] applied an International CAPM with constant betas and confirmed that both local and global factors affect equity returns. Further studies found that these risk exposures change over time and that the world price of covariance risk is not constant (Harvey, 1991).

Ferson and Harvey (1993) developed a model in which betas are characterized as functions of macroeconomic variables. On the other hand, Bekaert and Harvey (1995) varied the model to capture time-variation in beta coefficients and market risk premium. Ramchand and Susmel (1998) examined the Conditional International CAPM, allowing the market returns to depend on a world risk factor using a two-state Markov-switching model. Even though there are differences between the parameter's estimation in these models, they all try to capture time variation in betas and market risk premium.

[32] The assumption in International CAPM is that in globally integrated markets, the conditional expected return on a portfolio of stocks from a market is explained by the market's world risk exposure.

Additional studies show that a portfolio of stocks with specific attributes tends to perform better than the market as whole (see, e.g. (Banz, 1981; Basu, 1983)).[33] An alternative set of asset pricing models considers how well certain attributes of the underlying portfolio of stocks explain asset pricing anomalies[34] that are not explained by CAPM (Fama & French, 1992, 1993, 1996).[35] According to the theory of efficient markets,[36] these return differentials might be caused either by (1) market prices that are not efficient for an extended period, or (2) a single-factor model such as CAPM failing to appropriately measure risk. Given that the first is unlikely, financial economists began to criticise the CAPM, leading to the development of an alternative approaches such as Arbitrage Pricing Models (Roll & Ross, 1980; S. A. Ross, 1976).[37]

Notwithstanding its critiques (Bornholt, 2013; Dempsey, 2013), the CAPM remains appealing in finance, and many academics and managers prefer to use it (Bancel & Mittoo, 2014; Welch, 2008). The reason for its continued application is that it can be modified to incorporate a variety of explanatory/instrumental variables as well as various techniques for estimating the parameters of the model. The focus of this chapter is on incorporating an alternative estimation technique for a conditional CAPM to model time-varying betas in emerging markets.

Unlike previous studies on the conditional CAPM that employ instrumental variables to capture time variation in betas (Harvey, 2001), we apply a state-dependent specification in the Markov-switching framework, to measure structural changes in betas. More precisely, we address the following question: does accounting for market phases (i.e., time-varying volatility in equity risk premium) better contribute to explaining expected returns in emerging equity markets? we

[33] Recently, Harvey, Liu, and Zhu (2016) studied major risk factors in the finance literature that can explain the pattern of asset returns, and found that most of the identified risk factors in asset-pricing tests are likely false because the usual cut off levels for statistical significance may not be sufficient.
[34] An asset pricing anomaly is a statistically significant difference between the realized average returns associated with specific characteristics of securities or portfolios of securities formed by those characteristics, and the returns that are predicted by a particular asset-pricing model (Brennan & Xia, 2001).
[35] A wide variety of empirical factors has been tested in practice. One strand of these alternative models attempts to identify a set of economic influences that capture the investment risks (example of these macroeconomic factors are industrial production, inflation, interest rate and oil price (Chan et al., 1985; Chen et al., 1986; Sweeney & Warga, 1986)).
[36] A market in which prices always "fully reflect" available information is called an efficient market (Fama, 1965, 1970, 1991), though different degrees of efficiency exist.
[37] It is also important to note that extended models such as Carhart (1997) were outside the scope of this thesis. This thesis focussed on fit and predictability of the SD International CAPM model which were superior to the international Fama-French and Carhart models.

incorporate robustness checks of the results by incorporating global risk factors to test whether time-varying value and size effects can further explain expected returns.

This chapter contributes to the empirical literature on the Conditional International CAPM first by accounting for time variation in betas relating to distinct volatility changes in the equity premium, and second, by studying the predictive power of the model during different market phases.[38]

With regard to time-varying volatility in the equity risk premium and in betas, this study is informed by a number of previous studies which find that structural changes in market volatility are associated with different market phases (Abdymomunov & Morley, 2011; Chen et al., 2012; Chen & Huang, 2007; Huang, 2000, 2003; Vendrame et al., 2018).[39] If structural changes in market volatility are priced by market participants, we should expect the equity risk premium to change structurally. Following the assumption of the conditional CAPM, changes in betas related to structural changes in the market risk premium might explain some of the contradictions that exist in empirical investigations of the unconditional CAPM.

To measure the structural change in the equity risk premium, we adopt the Kim et al. (2004) model. First, we assume that market volatility follows a state-dependent process, with the equity risk premium varying between low volatility and high volatility states. Second, we consider that the information processing about the predominant volatility state causes a volatility persistence that needs to be addressed in order to explain the positive underlying relationship between market volatility and the market risk premium. A time-varying risk premium, or volatility feedback effect, occurs when an exogenous change in market volatility brings more return volatility as the stock prices react to new information about future expected returns. If market volatility is persistent and directly corresponds to the equity premium, we should expect stock prices to move in the opposite way to the market volatility level (Campbell & Hentschel, 1992). It is therefore essential to consider volatility feedback to reveal a positive relationship between market volatility level and equity risk premium.

Firstly, we find that some emerging markets exhibit time-varying volatility depending on world market phases. Secondly, we find that the predictive power of the SD International CAPM is

[38] We identify the market phases as the world total return index reported MSCI, which is a common benchmark for world equity returns.
[39] Moreover, Hamilton and Susmel (1994) find that persistent low frequency changes in market volatility can be modelled by a state-dependent model.

stronger during financial recessions but is weak during expansions. Thirdly, although the predictability of global risk factors identified by Fama and French is strong in a single state model, their explanatory power is small and limited when the conditional three-factor model with the state-dependent condition is used. The analysis using the state-dependent model provides more sophisticated estimates by distinguishing between high and low volatility states. This study finds that markets with a lower degree of integration may be priced locally; hence, investors can optimize their returns by investing in these markets. These findings have significant implications for the development of asset pricing models, portfolio management, and risk-return behaviour for investors interested in opportunities available in emerging markets, as well as for scholars who study international aspects of financial theory and practice.

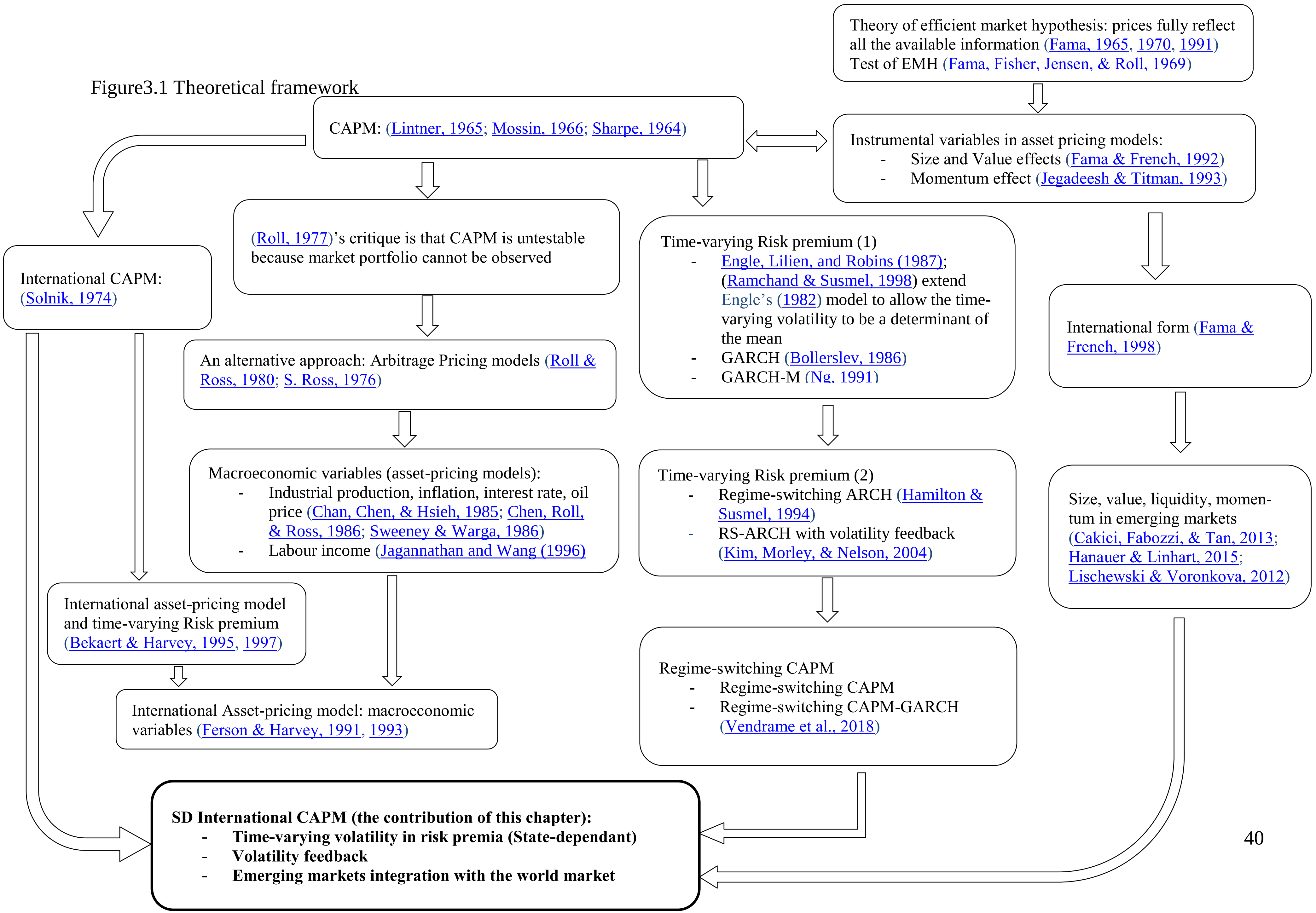
This chapter is organized as follows: Section 2 reviews the literature and hypotheses. Section 3 describes the methodology that applies, and Section 4 explains the data selection and discusses the empirical findings. The conclusions will be presented in Section 5.

3.2 Literature Review and Hypothesis Development

This section gives an overview of the development of CAPM and relevant studies that incorporate a state-dependent CAPM, then reviews the theoretical background underpinning the concept of a time-varying market risk premium and the development of hypotheses for this study.

Figure3.1 depicts the theoretical framework and supporting literature that lead to the development of the SD International CAPM used in this chapter.

Figure3.1 Theoretical framework



3.2.1 The CAPM

The CAPM assumes a linear and stable relationship between asset returns and market risk premium (Sharpe, 1964). The standard CAPM states that an asset's expected return should be comprised of the risk-free rate of return and a return associated with the market risk premium, where the market risk premium is the additional return over the risk-free rate in an economy and reflects the risk associated with the overall market. Under CAPM, asset returns move consistently with the overall market return, with the extent of the movement dependent on the asset's beta. The standard CAPM assumes that the asset's returns over time will behave in the same way regardless of changes in market conditions; in other words, the beta is stable. Consequently, the standard CAPM cannot capture changes in the behaviour of an asset during different market conditions, for example during an economic recession or an economic expansion.

Early empirical studies advocating the CAPM include Jensen, Black, and Scholes (1972), Blume and Friend (1973) and Fama and Macbeth (1973), but there are further studies which find that such models cannot explain certain asset pricing anomalies. However, the model consistently shows that the intercept is greater than the risk-free rate and the coefficient of beta is less than the average excess market returns (Fama & French, 1992; Fama & Macbeth, 1973; Jensen et al., 1972). Further research confirms earlier evidence that the relation between average returns and beta is much flatter than the Sharpe-Lintner's model predicts (Fama & French, 2004).

An important decision in the implementation of the CAPM is the choice of a market portfolio proxy, which may turn out to be mean-variance inefficient (on the Markowitz efficient frontier). According to Roll (1977), beta is always positively related to averaged individual returns, if the market proxy is on the positively sloped frontier, and the value of beta depends on the market proxy. Several studies have selected a market portfolio proxy limited to only US data, which may not truly represent a global risky asset portfolio. These studies then assumed that the market portfolio proxy was correlated with the true market portfolio; however, Roll (1977) concluded that the use of a market portfolio proxy has important implications for the testing of the CAPM and in the evaluation of portfolio performance. This issue is referred to as a benchmark error, because the actual purpose of the CAPM is to compare the performance of a managed portfolio with an unmanaged portfolio of equal risk (Roll, 1980, 1981). Roll indicated that if the benchmark is inappropriately specified, we cannot evaluate the performance of the portfolio manager. Roll's critique does not necessarily invalidate the CAPM as a principal model of asset pricing; it only requires an analysis of whether the market portfolio proxy is mean-variance efficient and whether it is the real optimum proxy.

The critiques of the empirical failure of the CAPM are along three lines. The first line of studies addresses misspecification of the linear two-factor models. Studies such as Fama and French (1993) and Roll and Ross (1980) propose a multifactor model. The second line of studies argues about the design and implementation of the empirical test, see for example (Kothari, Shanken, & Sloan, 1995) on survivorship bias issues.[40] The final line of these studies considers the possibility that the market risk premium and betas vary over time.

One of the shortcomings of the standard model is its disregard of time variation in the market risk premium.[41] To accommodate this behaviour in market risk premium and betas, various versions of the CAPM that allow beta to change over time were developed (see e.g., Jagannathan and Wang (1996); Lettau and Ludvigson (2001); Fama and French (2006); Lewellen and Nagel (2006); Ferson and Harvey (1999); Ang and Chen (2007)).

Jagannathan and Wang (1996) responded to the problem by proposing a new adjustment to the CAPM that allows beta and the market risk premium to vary over time depending on a predetermined variable (specifically, the variation in labour income, which is commonly known as conditional CAPM).[42] The conditional CAPM has attracted more attention in the literature, providing evidence that betas and market risk premium vary over time.[43] For example, Lewellen and Nagel (2006) argue that tests of the conditional CAPM cannot explain stock price anomalies such as the book-to-market ratio or momentum, and if the conditional CAPM holds, the deviation from the unconditional CAPM depends on the covariance between betas, equity premium and market volatility.

The CAPM has progressively evolved to include more sophisticated multifactor variants as additional risk factors were identified. The main factors that appear to have a consistent effect

[40] The first two are not related to the scope of this study.
[41] The market risk premium is defined as the expected return on a market portfolio in excess of the risk-free assets. It is also known as the "equity risk premium", the "equity premium", or the "risk premium". There is an assumption that a positive relationship exists between volatility and market risk premium; however, this is not a strict implication of modern general equilibrium of asset-pricing models (Kim et al., 2004).
[42] See also Iqbal, Brooks, and Galagedera (2010) for a test of the conditional CAPM with an emerging market perspective.

on stock price returns include the earning-price ratio (Basu, 1977), size factor (Banz, 1981), debt-equity ratio (Bhandari, 1988), liquidity (Amihud & Mendelson, 1986), book-to-market equity ratio (Rosenberg et al., 1985) and momentum effect (Jegadeesh & Titman, 1993). The three-factor model of Fama and French (1996), which contains size and value risk factors, along with Carhart's (1997) model, which includes the momentum effect, are now well accepted models. Additionally, more than fifty predictive variables have been documented as explaining asset pricing anomalies (Subrahmanyam, 2010). Recently, Fama and French (2015) identified two additional factors, profitability and investment patterns, that also contribute to explaining asset pricing behaviour.

Early empirical studies such as Blume (1971), Chen (1981), Fabozzi and Francis (1978), (Ferson & Harvey, 1991, 1993), Ferson and Korajczyk (1995) reported that the estimated market risk premium tends to be volatile and time-varying, and that the beta coefficients are time-variant. Therefore, the use of the ordinary least square (OLS) method in investment and portfolio analysis will yield an invalid estimate for systematic risk.

Similar studies which incorporate a state-dependent model to capture time-varying market risk include (Huang, 2000, 2003), who argues that the hypothesis of two states cannot be rejected. Huang (2003) investigates the time-varying systematic risks for ten single stocks, but he does not relate it to market volatility or the market phases. Chen and Huang (2007) suggest that in the estimation of the International CAPM, we should account for the changes in systematic risks over time. Abdymomunov and Morley (2011) jointly model the market risk premium and portfolio returns using a two-state CAPM. They allow the market risk premium to vary between high volatility and low volatility states while capturing the volatility feedback effect. They find that time-varying systematic risk can better explain portfolio returns than the unconditional systematic risk, especially when market volatility is high. Chen et al. (2012) propose time-varying market betas in the CAPM using a smooth transition regime switching CAPM with heteroskedasticity. They show that the model is strongly preferred over alternatives such as CAPM–GARCH. This is because while positive and negative shocks produce different volatility phases, and volatility is more affected by negative shocks than by positive shocks, GARCH models respond symmetrically to positive and negative shocks. More recently, Vendrame et al. (2018) have developed a conditional CAPM assuming that betas and risk premiums are time-varying subject to bull and bear market states. They find strong support for the conditional CAPM with beta explaining both bull and bear markets.

In this study, we follow the Abdymomunov and Morley (2011) approach by investigating time variation in CAPM betas that are driven by the probability of market volatility states. More precisely, we allow betas and the market risk premium to vary between low volatility and high volatility states. However, the approach in this chapter differs from the above studies in two ways. First, we examine the level of volatility of emerging markets relative to the world capital markets as one of the applications of the International CAPM. Second, we test the validity of an SD International CAPM against the standard form of the International CAPM in the case of emerging markets to check whether this model can better explain expected returns. More precisely, we model the volatility feedback effect that has been investigated in several previous studies in emerging markets and investigate whether this is related to world market phases. Third, we carry out robustness checks on the results, using the global three-factor model to test whether the state-dependent factor model can further explain expected returns in emerging equity markets.

3.2.2 Emerging Markets Research on Asset Pricing Models

Research in emerging markets has focused on various characteristics/risk factors that affect the expected returns (Fama & French, 1998; Griffin, Ji, & Martin, 2003; Rouwenhorst, 1999), with some studies producing mixed results (Cakici et al., 2013; Hanauer & Linhart, 2015; Lischewski & Voronkova, 2012). Bruner et al. (2008) show that asset pricing models with domestic factors appear to contain more information because some emerging markets exhibit a downward trend in their level of integration and become less integrated with world markets. Other studies test the International CAPM for partially-integrated markets (Arouri et al., 2012; Blitz et al., 2013; Tai, 2007). Further research developed an asset pricing model allowing the degree of integration with the world capital markets to switch over time (Bekaert & Harvey, 1995, 1997). Building on the previous literature, we develop and test an alternative version of the International CAPM in which the market risk premium switches based on the degree of volatility in world market returns.

Some studies have examined various characteristics of stock returns in emerging markets. Bekaert and Harvey (1995) developed an asset pricing model allowing emerging markets' degrees of integration with the world capital markets to vary across time, and Cheng, Jahan-Parvar, and Rothman (2010) tested this model considering the existence of a positive risk-return relation in stock returns. Bruner et al. (2008) showed that the choice of market portfolio, home country or global index, is essential to determining the pricing of asset and market integration.

The empirical evidence that concentrates on market premium, value and size effects in emerging markets has led to various conclusions. Notable examples include Fama and French (1998), who find that “value stocks” that have a higher book-to-market ratio earn higher returns than growth stocks that have a lower book-to-market ratio. Griffin et al. (2003) study the momentum effect across different economic climates and find positive international momentum profits. Rouwenhorst (1999) finds a similar pattern in stock returns behaviour and risk factors in emerging markets to those that have been found in developed markets. In addition, Lischewski and Voronkova (2012) investigate whether market, size, value and liquidity are priced risk factors. Despite the evidence that the market factor, size, and book-to-market value factors all have explanatory power, they do not find evidence supporting the idea that liquidity is a priced risk factor.

In contrast, Cakici et al. (2013) argue that there is strong evidence for the value effect in all emerging markets, but for the momentum effect in only some emerging markets. They find that local factors can explain asset return behaviour better than global factors, indicating that emerging markets are still segmented and that asset pricing models with domestic factors appear to contain more information than models with global factors, because some emerging markets exhibit a downward trend towards integration with world markets (Bruner et al., 2008).

We contend that the lack of significance of global factors may be due to different market conditions. The contrary evidence indicates that adjusting for time-varying volatility across different market conditions (i.e. high volatility and low volatility market conditions) and adjusting for time-varying market risk may produce useful pricing information with the global factors. Thus, this chapter adds a further investigation to these findings by using global value and size factors across different market phases to check whether this helps to explain stock return behaviour in emerging markets. In addition, we test the validity of the state-dependent three-factor model in emerging markets, based on volatility in the market risk premium.

3.2.3 Hypothesis Development

There is extensive research that has examined the relationship between conditional expected returns and conditional variance, both at the individual stock level and at the market level. The finding of many of these studies is that current and past asset returns are negatively correlated with future volatility. In other words, there is an asymmetric relationship between volatility and asset valuations: volatility tends to be lower when asset prices rise and higher when asset prices fall (Black, 1976). However, the findings in the literature are unsettled. For example, Bae, Kim, and Nelson (2007), Campbell and Hentschel (1992) and French, Schwert, and Stambaugh (1987) find a positive relationship between conditional expected return and conditional variance, whereas Nelson (1991) and Glosten et al. (1993) find a negative relationship.

Two theoretical explanations have been proposed to explain asymmetric volatility in market risk premium and hence in systematic risk. Typically, a decrease in asset prices is coupled with increased volatility. The term “leverage effect” refers to one possible economic explanation for this phenomenon: a drop in asset prices will cause the debt to equity ratio to increase, which makes the asset riskier; this drives up volatility in asset prices for investors (Black, 1976; Christie, 1982). The reason for this is that when the asset price of a company that uses debt and equity to finance its operations drops, this increases the debt to equity ratio, which will in turn lead to higher volatility in asset prices. Higher volatility further drops the asset price and increases leverage (Christie, 1982). In other words, all other things being equal, bad news leads to a higher leverage ratio, which in turn leads to increased volatility.

There is a negative correlation between asset prices and changes in volatility; assets with lower prices than expected tend to have high volatility and assets with higher prices than expected tend to have low volatility. As a result, it is natural to expect that these assets become riskier. This interpretation has been widely adopted in the literature to explain this behaviour in financial time series (Bollerslev, 1986; Engle, 1982).[44] However, the size of this effect appears to be too large to be explained only by financial leverage (Figlewski & Wang, 2000). Additionally, the asymmetric volatility is larger for the aggregate market index than for individual assets (Tauchen, Zhang, & Liu, 1996).

An alternative explanation for asymmetric volatility is a “volatility feedback” effect, also known as time-varying volatility, which relies on volatility clustering to explain the phenomenon. The volatility feedback effect states that these large shocks, either positive or negative, cause high volatility, and that leads to another period of high volatility. If volatility is priced into asset returns, an expected increase in volatility requires an increase in the rate of

[44] For instance, recently Christensen et al. (2015) investigated the impact of financial crisis on major developed and international equity markets, confirming the increase in leverage effect. They have also found that the leverage effect is negative during financial crisis.

returns on assets, which can only be expected by a decrease in asset prices (Campbell & Hentschel, 1992; Pindyck, 1984; Wu, 2001). More precisely, a large shock or bad news drops the asset price and drives up future volatility, which eventually pushes to lower the asset price; hence, this process maximizes the effect of bad news. If market volatility persistently and directly corresponds to the equity premium, we should expect stock prices to move in the opposite way to the market volatility level (see, e.g., Campbell and Hentschel (1992)). Similarly, good news increases both asset price and future volatility, but higher volatility has an adverse effect on asset price, and that reduces the impact of the good news.

While the leverage effect hypothesis argues that a negative return makes the company more leveraged, and as a result riskier, and hence leads to higher volatility; the volatility feedback hypothesis, however, reverses the causality, arguing that increases in volatility are associated with future negative returns. These two explanations of negative and asymmetric correlation between asset return and volatility differ in the direction of causality and how volatility responds to positive and negative shocks. Empirical tests on these alternative hypotheses have been widely investigated and evaluated (Bekaert & Wu, 2000). However, the direction of causality remains an open question.[45]

Kim et al. (2004) find that invoking an information assumption that allows for volatility feedback produces statistically significant evidence of a positive relationship between market volatility and equity risk premium. To measure time-varying volatility in equity risk premium, this chapter adopts the Kim et al. (2004) model, first by assuming that market volatility follows a state-dependent process with the equity risk premium varying between low and high market volatility states, and second by considering that the information processing about the predominant volatility state causes a volatility feedback effect that should explain a positive underlying relationship between market volatility and the market risk premium. It is more robust to estimate the true sign of the relationship between market volatility and the equity risk premium with the presence of volatility feedback effect (Kim et al., 2004).

[45] For example, Bollerslev, Litvinova, and Tauchen (2006) use higher frequency data to construct realized volatility proxies over longer horizons. They find: 1) negative correlation between the volatility and the current and lagged returns, which lasts for several days; 2) low correlations between the returns and the lagged volatility; and 3) strong correlation between the high-frequency returns and their absolute values. Their findings support the dual presence of a prolonged leverage effect at the intraday level and an almost simultaneous volatility feedback effect. Bollerslev, Osterrieder, Sizova, and Tauchen (2013) developed a representative agent model based on recursive preferences to generate a volatility process, which exhibits clustering and fractional integration, and has a risk premium and a leverage effect.

Based on the above discussion, we infer that there are statistically significant changes in market volatility and equity risk premiums at different times and that this causes overestimation (underestimation) of estimated expected returns from International CAPM. Thus, we test the following hypothesis to check whether capturing time-varying volatility in equity risk premium can better explain expected returns in emerging markets.

Hypothesis 1: Higher volatility in the equity risk premium is associated with lower expected returns and lower volatility in the equity risk premium is associated with higher expected returns.

The most popular econometric method for dealing with asymmetric volatility is via ARCH-type models.[46] The main criticism of these models is that they assume the process of volatility response to multiphase shocks to be constant, by fixing the coefficient that generates the conditional volatility. A newer class of multivariate models called dynamic conditional correlation (DCC-GARCH) models was proposed by Engle (2002). These have the flexibility of univariate GARCH models, coupled with parsimonious parametric models for correlations. However, as discussed above, financial time series generally display structural changes in their behaviour that are initially caused by structural changes that cannot be characterized by univariate or multivariate ARCH-type models (Cai, 1994; Hamilton & Susmel, 1994). If the ARCH-type models are used on a time series that presents time-varying volatility and these structural changes are not controlled for, this will cause a substantial overestimation of the autoregressive parameters of the conditional variance (Hillebrand, 2005). Since the time-varying volatility in equity risk premium causes significant changes in parameter estimations, a state-dependent model can give a better estimate of the behaviour of equity risk premium and hence expected returns on an asset or portfolio and answer the research question for this chapter.

[46] To deal with time-varying volatility in market returns, autoregressive conditional heteroskedasticity (ARCH) models have been introduced in the econometrics literature, starting with Engle (1982) and followed by a generalized ARCH (GARCH: Bollerslev (1986)). It is also recognized that positive and negative shocks produce different impacts: volatility is more affected by negative shocks than by positive shocks. Indeed, the econometric models such as ARCH and GARCH are preferable because they account for volatility persistence and volatility feedback[46]. But these models assume the specific risk (idiosyncratic risk) to response symmetrically to positive and negative shocks, an approach with weaker practical outcomes. Some studies have developed structural-time models to account for this asymmetric effect (e.g., see Nelson (1991) model, known as Exponential GARCH, and Glosten et al. (1993) model, known as GJR-GARCH). These models have been broadly applied in finance when testing asset-pricing models.

Hypothesis 2: A state-dependent model that accounts for time-varying volatility in the equity risk premium is more beneficial than a GARCH model for explaining asset pricing behaviour in emerging markets.[47]

In modelling the risk premium, a state-dependent approach with a volatility feedback effect offers two advantages over other alternatives such as the broadly-employed ARCH-type specifications (Kim et al., 2004). In a study of weekly equity returns, a state-dependent model with ARCH specifications has been found to die out most of the ARCH dynamics (Hamilton & Susmel, 1994); however, the state-dependent changes persist over longer horizons. Several other studies (Abdymomunov, 2013; Augustyniak, 2014; Schaller & Norden, 1997). More recent studies have found that the return volatility is directed to two distinct states, where the high-volatility state corresponds to a period of crisis or financial uncertainty and the low-volatility state corresponds to a period of market expansion (Augustyniak, 2014; Bensaïda, 2015; Christensen et al., 2015; Wilfling, 2009). In a similar manner, these structural breaks in return volatility could be the result of a fluctuation in investors' perceptions. Even allowing for the fact that investors are given similar information, the trading activities and risk-taking behaviour may be different during (crisis) periods of the crisis with higher volatility (Hoffmann, Post, & Pennings, 2013).

Recently there have been some attempts to combine the two dynamic processes, the ARCH specification and a Markov model, in which these models introduce more parameters estimates and in return generate process (Augustyniak, 2014; Christensen et al., 2015).[48] However, using these combined approaches may not necessarily improve asset pricing models and may only capture the high spikes in asset returns, which may be appropriate when adopted on high-frequency data, such as daily or hourly.

By only capturing large structural changes in market volatility (Hamilton & Susmel, 1994), a state-dependent model offers further assurance than does an ARCH-type model that we model the volatility feedback effect and not the leverage effect. The leverage effect hypothesis states that large shifts in asset prices change the debt-to-equity ratio of companies, swinging the risk

[47] The rationale of this thesis was to investigate the suitability of state-dependent models in emerging markets. Therefore, this hypothesis is developed to make a comparison between State-dependent asset pricing models with current models that extensively used in both developed and emerging markets. Results in Table 3.9 and Figure 3.4 and 3.5 are responses to this hypothesis.

[48] See also Wilfling (2009) for student's *t* distribution and Bensaïda (2015) for the skewed generalized *t* distribution.

profile, and therefore leading to the higher future volatility of returns. In this case, the direction of causality is reversed to what the volatility feedback is, while the size of volatility changes being dependent on the size of price changes (Bekaert & Wu, 2000). Therefore, If the leverage effect hypothesis was the leading cause of the negative relation between volatility and realized returns, we should expect to see ARCH effects in the residuals from a model that only captures large structural changes in market volatility (Kim et al., 2004). Thus, state-dependent models are better suited to model volatility feedback.

The method of testing the SD International CAPM with volatility feedback to model asset pricing returns has three advantages compared to the traditional International CAPM. First, we do not incorporate exogenous observable variables to determine time variation in the equity premium: hence, the model is parsimonious compared to the instrumental variables approach. Second, time variation in betas relating to the changes in the equity premium is identified directly by the market returns through the state-dependent specification, rather than being imposed exogenously. This approach has an advantage compared to a rolling window estimate that eventually smooths out structural changes in beta and in which estimates rely highly on the choice of window length. Third, this approach is on the basis of a time series regression test, in comparison to the cross-sectional approach applied in previous studies, and thus is not subject to the restrictions of the cross-sectional approach mentioned in Lettau and Ludvigson (2001).

3.2.4 Fama and French Factor Model

In addition to the equity risk premium, Fama and French (1993) propose two additional risk factors that can partially explain asset pricing returns to capture pervasive risks in asset returns. These risk factors capture risks associated with firm size and the returns differential associated with growth and value stocks. The SMB (small minus big) risk factor proxy captures the higher systematic risk between a portfolio of small-capitalization stocks and portfolio of large stocks; the HML (high minus low) risk factor proxy captures the systematic risk between a portfolio of high book-to-market values and low book-to-market values. Fama and French's (1993) model argues that size and book-to-market factors justify the failure of CAPM. They suggest that a firm's value and size are proxies for non-diversifiable risk factors. They also find that the returns of high-value stocks and small size stocks tend to change in the same manner, which is indicative of a common risk factor.

In contrast, numerous studies argue that the return premia on small size stocks and high-value stocks do not indicate the correlation of these stocks with risk factors; instead, it is the stock characteristics that seem to explain the variation in stock returns. For example, Lakonishok, Shleifer, and Vishny (1994) find that value stocks yield higher returns because they are underpriced relative to their risk and return characteristics and not because they compensate for higher systematic risk. Daniel and Titman (1997) reach a similar conclusion: that it is the stocks' characteristics and not the covariance structure of returns that help to explain the variation in stock returns. Moreover, in portfolios that are selected based on their return characteristics, these portfolios are useful risk factors even if these characteristics are not related to risk (Ferson, Sarkissian, & Simin, 1999). Indeed, if the size and value effects are because of underpricing and irrelevant to risk, it should not disprove the validity of the CAPM in various applications. In this study, we aim to use the value effect and the size effect as two risk proxies on different emerging market portfolios, sorted to test whether these factors help to explain the variation in stock returns.

Hypothesis 3: The size and value effects can help to explain asset pricing returns in emerging markets.

The time variation in expected returns that is dependent on the state of the economy has been documented for value and momentum effects by Chordia and Shivakumar (2002) and Stivers and Sun (2010), using macroeconomic state variables. Gulen, Xing, and Zhang (2011) find evidence that the value premium is time-varying by applying a two-state Markov switching model with the interest rate to determine time-varying transition probabilities. Angelidis and Tessaromatis (2014) find evidence that value, size and momentum factors are state-dependent, and these factors yield positive and significant returns in a low variance state. In this study, we further investigate time-varying global size and value factors with the market risk premium to determine the transition probabilities. More precisely, we test whether time-varying global factors are state-dependent and help to explain the behaviour of asset returns in emerging markets.

Hypothesis 4: The size and value effects incorporating time-varying volatility can better explain asset pricing returns in emerging markets.

3.3 Method

The methodology in this chapter is developed based on the state-dependent risk premium of Kim et al. (2004), the conditional CAPM of Jagannathan and Wang (1996) and the SD CAPM of Abdymomunov and Morley (2011). Extending their approaches to the SD International CAPM as well as the state-dependent factor model, we begin by introducing the regression form of CAPM with GARCH (1,1), which is used as a benchmark for this study.

3.3.1 International CAPM–GARCH (1, 1)[49]

In the absence of exchange rate risk, the empirical test of the International CAPM applied in the literature has the following regression form:

$$r_{i,t} = \alpha + \beta r_{m,t} + \varepsilon_{i,t} \qquad \varepsilon_{it} \sim N(0, \sigma_{it}^2) \tag{3.1}$$

Where $r_{i,t}$ is the excess return for each equity market i, $r_{m,t}$ is the world market excess return, and $\varepsilon_{i,t}$ is the white noise innovation process given by:

$$h_{it} = \omega + \alpha\varepsilon_{it-1}^2 + \beta h_{it-1} \qquad \varepsilon_{it} \sim N(0, h_{it}) \tag{3.2}$$

Where h_{it} is the conditional variance for day t, ω, α and β are the coefficients of the GARCH (1,1) and ε_{t-1}^2 is the mean equation squared residual for day t. Several studies have argued about the importance of modelling time-varying volatility in financial time series. The ARCH model of Engle (1982) and one of its extensions, generalized autoregressive conditional heteroscedasticity (GARCH: Bollerslev (1986)), have been successfully used to model time-varying volatility in financial time series.[50]

The GARCH (1,1) specification means that tomorrow's volatility is the square of today's residuals, so the sign of the residual does not affect the volatility forecast. The GJR-GARCH model of Glosten et al. (1993) corrected for this effect. In their specification, the effect of tomorrow's volatility is negative if today's residual is negative and vice versa. An alternative

[49] The CAPM with GARCH estimates used here as a benchmark only. This is consistent with previous research such as Ramchand and Susmel (1998) who tested the regime-switching CAPM and compared it with CAPM-GARCH.

[50] Ng (1991) focuses on a multivariate GARCH approach and finds significant time-variation in betas.

specification is the Exponential GARCH model of Nelson (1991), where the conditional variance (the logarithm of conditional variance) allows the sign and the magnitude of residuals to have separate effects on volatility. However, asset returns generally display sudden shifts in their behaviour, which cause time-varying volatility in returns and cannot be characterized by single-state GARCH-class models. This chapter incorporates an alternative specification for the analysis of time-varying volatility when testing asset pricing models.

The model in equation (3.1) implies that expected excess return on portfolio (return on asset minus risk-free rate) is fully explained by its expected CAPM risk premium (the beta times expected value of market risk premium). This reflects the assumption that the intercept term, α_i, in the time-series regression is zero for each portfolio, and the error terms ε_{it} are assumed to be symmetrically distributed around zero. The early evidence from this version of the model shows a positive relation between beta and average expected returns.[51]

3.3.2 State-dependent International CAPM

According to the Sharpe-Lintner CAPM, the expected return on a portfolio over the risk-free asset depends on the measure of a portfolio's risk relative to the market portfolio. More precisely, let $r_{i,t}$ and $r_{m,t}$ be real-valued observations for returns on an asset and market portfolio over the risk-free rate during a specific time and let β_i^m be the portfolio's beta:

$$E[r_{i,t}] = \beta_i^m E[r_{m,t}] \tag{3.3}$$

Where E represents an expectation. β_i^m can be expressed as the covariance between the return on portfolio i and the world market returns, standardized by the variance of the world market returns.

$$\beta_i^m = \frac{Cov(r_{i,t}\,, r_{m,t})}{Var(r_{m,t})} = Cor(r_{i,t}\,, r_{m,t}) \times \frac{\sqrt{Var(r_{i,t})}}{\sqrt{Var(r_{m,t})}} \tag{3.4}$$

In equation (3.4), three elements define β_i^m: the correlation between portfolio i and the world market portfolio, the volatility of portfolio i and the volatility of the world market portfolio. The required rate of return on a portfolio over the risk-free rate is equal to its beta times the expected returns on the market portfolio over the risk-free rate. Note that in this study, the

[51] However, further research illustrates that the relation between beta and average return is too flat when portfolios are sorted on price ratios (Jensen et al. (1972) and Stambaugh (1982)).

assumption is that equity markets are integrated; thus, we use a global factor to drive market volatility. Accordingly, equation (3.3) is defined as International CAPM.

Fama and French (1992) empirically examine the performance of the CAPM-given equation (3.3) and find that estimated betas do not explain variations in expected returns for different portfolios. They interpret the results as a flat relation between expected returns and beta as the failure of CAPM. One possible reason for this failure is that market risk premium and betas are likely to vary over time. Following the assumption of the conditional CAPM, if any changes in betas are related to the structural changes in market volatility, this might explain the failure of the empirical investigation of the unconditional CAPM (Bodurtha & Mark, 1991). Adjusting for this, the conditional CAPM that holds period by period is defined as:

$$E[r_{i,t}|I_{t-1}] = \beta_{i,t-1}^{m} E[r_{m,t}|I_{t-1}] \tag{3.5}$$

Where I_{t-1} is information available to investors in previous the period and $\beta_{i,t-1}^{m}$is beta conditional on information available in previous period defined as

$$\beta_{i,t-1}^{m} = \frac{Cov(r_{i,t}, r_{m,t}|I_{t-1})}{Var(r_{m,t}|I_{t-1})}$$

The assumption in equation (3.5) is that investors price assets at time t based on the information available at $t-1$. Following Jagannathan and Wang (1996) and using iterated expectation on both sides of equation (3.3):

$$E[r_{i,t}] = \bar{\beta}_{\iota} E(r_{m,t}) + cov(\beta_{i,t-1}^{m}, E[r_{m,t}|I_{t-1}]) \tag{3.6}$$

where $\bar{\beta}_{\iota}$ is the conditional expectation of beta. If the beta is constant, this means that the covariance term is zero; then the above equation is equal to equation (3.3). However, in practice, the unconditional CAPM in equation (3.3) would be invalid if beta and the equity risk premium were correlated with each other.

Jagannathan and Wang (1996) also find that "alpha" from the regression form of the unconditional CAPM, where "alpha" corresponds to the expected excess return for the portfolio over what would be predicted by the unconditional CAPM, is theoretically related to the covariance between a time-varying beta and a time-varying equity premium and this covariance can partially explain some of the anomalies that found in previous studies.

Following Kim et al. (2004), we define the equity risk premium with two-state Markov-switching model as follows:

$$\varepsilon_{m,t} \sim N(0, \sigma^2_{m,S_{m,t}}) \tag{3.7}$$

$$\sigma^2_{m,S_{m,t}} = \sigma^2_{m,0}\left(1 - S_{m,t}\right) + \sigma^2_{m,1} S_{m,t} \tag{3.8}$$

$$\sigma^2_{m,0} < \sigma^2_{m,1} \tag{3.9}$$

Where $\varepsilon_{m,t}$ is the information available to investors at time t, $\sigma^2_{m,S_{m,t}}$ denotes the variance of $\varepsilon_{m,t}$, and $S_{m,t}$ indicates the state variable defined by the Markov-switching model, which can take value 0 in the low variance state and 1 in the high variance state to ensure that each state is correctly identified as a low or high variance state.

Following Hamilton (1994) Markov chain of order one for the estimation of the unobserved state variable, s_t, is assumed as:

$$Pr\{s_t = 0 | s_{t-1} = 0\} = p_m \tag{3.10}$$

$$Pr\{s_t = 1 | s_{t-1} = 1\} = q_m$$

Where $Pr\{s_t = i | s_{t-1} = i\}$ assumes that the transition probability state i is followed by state i. As a property of the Markov chain, this indicates that the process for s_t is assumed to depend on past observation only through s_{t-1}. The transition probability is the probability associated with various state changes and it measures the movement from one state to another (See Appendix A).

Assuming the two-state specification for volatility in excess market returns, the information assumption for the conditional CAPM is that investors know about the market volatility state. Based on this assumption and following Kim et al. (2004), the period-by-period equity risk premium is defined as:

$$E[r_{m,t} | S_{m,t}] = \mu_{m,0} + \mu_{m,1} \Pr[S_{m,t+1} | S_{m,t}] \tag{3.11}$$

Where $\mu_{m,0}$ is the equity risk premium in low variance state and $\mu_{m,1}$ specifies the marginal effect of equity risk premium in high variance state. Like the previous studies, this study finds a negative value for $\mu_{m,1}$ which, while not consistent with the theoretical view of a positive risk-return relationship, is consistent with the findings of much of the previous literature in the area. This evidence may indicate that although investors know about the prevailing volatility state, it may take time to process information about it. Kim et al. (2004) find that considering the information assumption that allows for volatility feedback provides statistically significant evidence of a positive relationship between market volatility and equity risk premium. According to the assumption of volatility feedback, an exogenous and persistent increase in market volatility brings more return volatility as stock prices react to new information about future expected returns. Therefore, considering volatility feedback is essential to reveal a positive relationship between market volatility and equity risk premium. It is more robust to estimate the true sign of the relationship between market volatility and the equity risk premium with the presence of volatility feedback effect, and to control for information processing (Kim et al., 2004). We therefore modify the model with volatility feedback, which is defined as follows:

$$r_{m,t} = E[r_{m,t} | I_{m,t-1}] + f_{m,t} + \varepsilon_{m,t} \tag{3.12}$$

Where

$$E[r_{m,t} | I_{m,t-1}] = \mu_{m,0} + \mu_{m,1}\Pr[S_{m,t} = 1 | S_{m,t-1}] \tag{3.13}$$

And following Kim et al. (2004):

$$f_{m,t} = \delta\{Pr(S_{m,t} = 1 | S'_t) - \Pr[S_{m,t} = 1 | S_{m,t-1}]\} \tag{3.14}$$

The $f_{m,t}$ term captures an unpredictable volatility feedback effect on the market returns due to period-by-period revision in future expected returns, where $E[f_{m,t} | S_{m,t-1}] = 0$. The δ is the volatility feedback coefficient defined as $\delta = \frac{-\mu_{m,1}}{1-\rho\lambda}$. In this specification, ρ denotes the parameters of linearization, which are the average ratio of the stock price to the sum of stock price and the dividend.[52] The positive price of risk indicates that the coefficient δ on the volatility feedback term will be negative, given the volatility states are persistent so that $\lambda = p_m + q_m - 1 > 0$ (Hamilton, 1989).[53] Conversely, any evidence of a negative volatility feedback effect implies a positive relationship between market volatility and the equity premium. Investors observe the previous volatility state $S_{m,t-1}$ at the start of the current period, time t, but know about the current volatility during the current period. This implies a positive relationship between market volatility and the equity premium (Appendix D).

Now, as for the market excess return portfolio, the excess return portfolio is defined as:

$$r_{i,t} = E\left[r_{i,t}\middle|S_{m,t-1}\right] + f_{i,t} + \varepsilon_{i,t} \tag{3.15}$$

Where $E\left[r_{i,t}\middle|S_{m,t-1}\right]$ denotes the conditional excess return on portfolio given in equation (3.5), $f_{i,t}$ is the volatility feedback term for the portfolio excess return and $\varepsilon_{i,t}$ is the news about portfolio i. Since the portfolio's risk β_i, may covary with the time-varying market risk premium, where the specification takes two different values depending on the market volatility states, we have two different values for beta in these two states. Note that following Huang (2003) and Chen and Huang (2007), an alternative specification is to allow beta to have its own state-dependent process. In my specification, we follow Abdymomunov and Morley (2011) by allowing common states for beta and market volatility. Now the state-dependent conditional CAPM is as follows:

$$E\left[r_{i,t}\middle|S_{m,t-1}\right] = \beta^{m}_{i,S_{m,t-1}} E[r_{m,t}|S_{m,t-1}] \tag{3.16}$$

Where $\beta^{m}_{i,S_{m,t-1}}$ is the portfolio's risk, which can take different values conditional on the market volatility state at time $t-1$. More precisely, the value of $\beta^{m}_{i,S_{m,t-1}}$ is dependent on the realization of $S_{m,t}$. Beta will be conditional on the sensitivity of its portfolio to market news for each state. In practice, given constant probabilities, this specification measures beta as a function of the state variable, $S_{m,t-1}$. This is equivalent to capturing the weighted-average

[52] Campbell and Shiller (1988) estimated the value of $\rho \simeq 0.997$ for US data where the average dividend price ratio has been about 4% per annum.

[53] Kim et al. (2004) estimate δ, with restriction, where $\rho = 0.997$ and $\lambda = p_m + q_m - 1$ to see if there is still positive relationship between US stock market volatility and the equity premium. However, the main objective of this chapter is to use these estimates to test the efficiency of International CAPM. In addition, we use world market data where the average dividend price ratio may vary from market to market.

sensitivity of the portfolio dependent on $S_{m,t-1}$. In addition, substituting for $r_{m,t}$ and $r_{i,t}$ from equations (3.12) and (3.15) into equation (3.16), we have

$$E\left[f_{i,t}\middle|S_{m,t-1}\right] = \beta^{m}_{i,S_{m,t-1}} E\left[f_{m,t}\middle|S_{m,t-1}\right] = 0$$

Which satisfies the assumption of the CAPM that expected excess return depends only on the portfolio's beta and the market risk premium.

From equations (3.12) and (3.16), we can jointly model the market and the excess return portfolios Abdymomunov and Morley (2011).

$$\begin{aligned} r_{m,t} &= \mu_{m,0} + \mu_{m,1}\Pr[S_{m,t} \\ &= 1|S_{m,t-1}] + \delta\{Pr\left[S_{m,t} = 1\middle|S_{m,t}\right] - \Pr\left[S_{m,t} = 1\middle|S_{m,t-1}\right]\} + \varepsilon_{m,t} \end{aligned} \tag{3.17}$$

$$r_{i,t} = \alpha_{i,S_{m,t-1}} + \beta^{m}_{i,S_{m,t-1}} r_{m,t} + u_t \tag{3.18}$$

$$\varepsilon_{m,t} \sim N(0, \sigma^2_{m,S_{m,t}}) \text{ and } u_t \sim N(0, \sigma^2_{i,S_{i,t}})$$

Where u_t is the idiosyncratic volatility for portfolio i and is assumed to be unrelated to the market volatility based on the theoretical assumption of CAPM, $r_{i,t}$ is the return on portfolio i and $r_{m,t}$ is return on market portfolio. If the conditional CAPM holds, $\alpha_{i,S_{m,t-1}} = 0$ in both states and $\beta^{m}_{i,S_{m,t-1}}$ is the coefficient measuring the systematic risk of the portfolio. Accordingly, the coefficient for state 1 is $(\alpha_{i,1}, \beta_{i,1})$ and for state 2 is $(\alpha_{i,2}, \beta_{i,2})$. Now the excess return of portfolio i is measured as being dependent on the excess return of the market portfolio. We control for heteroskedasticity in the residual for portfolio returns by assuming that the variance $\sigma^2_{i,S_{i,t}}$ in equation (3.18) follows two-state Markov switching process. This process is assumed to be independent of the market volatility (Abdymomunov & Morley, 2011).

In addition to state-dependent market volatility, we allow for heteroscedasticity in the residual for the portfolio return being state-dependent. Therefore, the conditional variance of residuals, σ^2_{i,S_t} is also dependent on the expectation of $S_{m,t}$ where: $\sigma^2_{\mathrm{i},2} > \sigma^2_{\mathrm{i},1}$ so that the variance can change between the two states. We estimate the parameters of equations (3.17) and 3.18 using the maximum likelihood estimation based on the Expectation Maximization Algorithm developed by Hamilton (1994) (Appendix B).

Fama and French three-factor model:

$$r_{it} = \alpha_i + \beta_i^m r_{m,t} + \beta_i^{smb} r_{smb,t} + \beta_i^{hml} r_{hml,t} + u_t \tag{3.19}$$

Similar to the market excess return, we now assume that the SMB portfolio excess returns and HML portfolio excess returns are time-varying and they are dependent on the expectation of $S_{m,t}$, which again is driven by market volatility. Therefore, we consider the same specification with common states for both value and size factors.

$$r_{smb,t} = E\left[r_{smb,t} \middle| S_{m,t-1}\right] + f_{smb,t} + \varepsilon_{smb,t} \tag{3.20}$$

$$r_{hml,t} = E\left[r_{hml,t} \middle| S_{m,t-1}\right] + f_{hml,t} + \varepsilon_{hml,t} \tag{3.21}$$

Where $E\left[r_{smb,t} \middle| S_{m,t-1}\right]$ and $E\left[r_{hml,t} \middle| S_{m,t-1}\right]$ are defined by the conditional factor-model, $f_{smb,t}$ and $f_{hml,t}$ are the volatility feedback terms for the portfolio returns, and $\varepsilon_{smb,t}$ and $\varepsilon_{hml,t}$ are the news about SMB and HML portfolios.

Now we can modify the Fama and French three-factor model by assuming that the value and size risk factors are time-varying and dependent on time variation in the market risk premium. Thus, the state-dependent conditional three-factor model is given by:

$$r_{it} = \alpha_{i,S_{m,t-1}} + \beta_{i,S_{m,t-1}}^m r_{m,t} + \beta_{i,S_{m,t-1}}^{smb} r_{smb,t} + \beta_{i,S_{m,t-1}}^{hml} r_{hml,t} + u_t \tag{3.22}$$

$$u_t \sim N\left(0, \sigma_{i,S_{i,t}}^2\right)$$

Where u_t is idiosyncratic volatility for portfolio i. $r_{smb,t}$ is excess returns on small size portfolios and $r_{hml,t}$ is the excess returns value portfolio. $\beta_{i,S_{m,t-1}}^{smb}$ and $\beta_{i,S_{m,t-1}}^{hml}$ take two different values conditional on market volatility state at period $t-1$. Similar to the assumption of the conditional CAPM, we consider a specification with common states for value and size risk factors.

3.3.3 Serial Correlation

Most of the excess return series show serial correlation, at a 5 per cent level of significance. The evidence of serial correlation indicates the need to encompass a higher order ARCH process (Giannopoulos, 1995). One common approach to deal with serial correlation is to adjust an autoregressive model using certain information criteria (Papavassiliou, 2013). In this chapter, the autoregressive model (AR) is incorporated into the asset pricing models where significant correlation is present.

Morse (1980) finds evidence of a positive relation between trading volume and serial correlation, which confirms the theory of asymmetric information; periods of high-volume trading are those in which the adjustment to new information is taking place, leading to positive autocorrelation in asset returns (Holden & Subrahmanyam, 2002). Ball and Kothari (1989) find that the negative serial correlation in return series is due mainly to variation in relative risks. Lebaron (1992), on the other hand, finds that serial correlations change over time and are related to the return volatility.

3.4 Data and Empirical Results

In this section, we first explain the data that is used and give descriptive statistics on the data and explanatory power of the SD International CAPM against the standard form of the International CAPM. More precisely, we model the volatility clustering that has been investigated in several previous studies in emerging markets. Second, we test whether the time-varying global size and value risk factors can better explain the expected returns in emerging markets.

3.4.1 Data

The emerging markets data in this chapter consists of the equity markets included in the MSCI emerging market indices. As of June 2014, the MSCI Emerging Market Index comprises the following 23 emerging market indices across four geographic regions: the Americas (Brazil, Chile, Colombia, Mexico and Peru), Asia Pacific (China, India, Indonesia, Malaysia, the Philippines, Taiwan, Thailand and South Korea), Europe (Greece, the Czech Republic, Hungary and Poland), and West Asia and Africa (Egypt, Qatar, Russia, South Africa, Turkey and the United Arab Emirates). These countries represent a total population of more than 4 billion as of December 2014, standing for a significant market in world business. Despite having different cultures, languages, economics and politics, there are common factors among these countries.

Financial data was collected from the Thomson Reuters Financials Datastream (TFD) data bank. We use weekly returns, calculated as the natural log of the total return for each value-weighted index. To maintain consistency of the results, weekly returns in USD were collected for all of the indices. The length of the sample is not uniform and depends on the availability of data. The data starts in January 2001 and ends in June 2016 for all the equity markets except for Qatar and the UAE, which begin in June 2005. The proxy for the world financial market index is the MSCI world total return index. To test Fama and French's (1993) three-factor model, we use the size risk factor proxy, being the difference between the return of the largest stocks and the return of the smallest, and the value stocks factor proxy, subtracting the return of firms with the highest book-to-market equity from the average return of those with the lowest book-to-market equity. All excess returns are calculated in relative to the one-month US T-bill rate.

Table 3.1 presents the summary statistics for the sample set. Panel A summarizes some characteristics of the excess return series for each of the equity markets. First, we note that those markets that yield more returns do not necessarily present higher volatility, suggesting that the long-term average positive risk-return relationship may not be present. Second, negative skew suggests that the return distribution is skewed to the left, implying that large negative returns are more likely to happen. Interestingly, the excess return distributions do not represent significant skewness, except for Brazil, Chile, Mexico and Qatar. Third, as a common factor of a financial time series, these markets exhibit a higher level of kurtosis than the normal value of 3. Accordingly, the distributions of the excess return series are leptokurtic and non-Gaussian.

Further, Jarque-Bera test statistics show that excess return series are not normally distributed. We perform the Augmented Dickey-Fuller (ADF)[54] unit root test of Dickey and Fuller (1981) at the logarithmic level. The associated test statistics are also presented in Panel B of Table 3.1. The result at the logarithmic level shows that all of the excess return series are integrated to the order of 1, since the result of the ADF test statistics is less than the critical value. Panel C of Table 3.1 reports autocorrelations for the return series. Negative serial correlation is observed for Chile, Greece, India, South Korea, Mexico, Pero, Poland, Russia and South Africa as well as the US. Negative autocorrelation highlights the presence of volatility feedback in most return series. The idiosyncratic noise makes it hard to detect a predictable pattern in the return series.

[54] ADF test is very common stationary test that still in practice and used in similar recent studies (Balcilar, Gupta, & Miller, 2015; Dai & Serletis, 2019; Walid, Chaker, Masood, & Fry, 2011).

Table 3.2 presents the summary statistics for independent variables as well as the correlation matrix. The SMB (small minus big), which accounts for size risk factor, is estimated as the difference between the return of the largest stocks and the return of the smallest and the HML (high minus low), which represents the value stocks, is calculated by subtracting the return of firms with the highest book-to-market equity from the average return of those with the lowest book-to-market equity (Fama & French, 1993). A negative value for HML implies that growth stocks outperformed value stocks as the results indicate. On the other hand, a positive SMB implies that small cap stocks outperformed large cap stocks during this period. The results for skewness and kurtosis for all of the three independent variables are consistently different from the standard normal distribution, and the Jarque-Bera test statistic strongly supports non-normality (Da Silva, 2006). The result at the logarithmic level shows that all the three independent variables are integrated to the order of 1. No significant correlation is detected among the independent variables. For example, correlation between the two mimicking returns, SMB and HML, is only -0.08. The low cross-correlations indicate that there is no problem of multicollinearity that significantly affects the estimated three-factor model (Carhart, 1997). The first four autocorrelations of these three independent variables are quite small and not significant at a 5 per cent level. However, there is some evidence of positive autocorrelations for SMB and HML at a lag of two weeks, which may be due to thin trading or as a result of investors responding to past information.

Table 3.1 Sample statistics for weekly excess returns for MSCI emerging market indices and the US.

All returns are expressed in USD and calculated in excess of the one-month US T-bill rate. The sample covers the period January 2001 to June 2016 for all indices except for Qatar and the UAE, which start in June 2005. The Jarque–Bera test for normality is based on skewness and excess kurtosis. ADF denotes Augmented Dickey-Fuller unit root test statistics. * denotes significance at a 5 per cent level.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Panel A - Descriptive statistics of excess returns												
Mean	0.0014	0.0013	0.0013	0.0035	0.0024	0.0021	-0.0035	0.0013	0.0017	0.0029	0.0018	0.0011
Std. Dev.	0.0500	0.0318	0.0399	0.0393	0.0388	0.0429	0.0595	0.0514	0.0390	0.0457	0.0436	0.0251
Skewness	-1.1382	-1.3927	-0.4941	-0.5629	-0.4882	-0.7124	-0.9305	-1.0236	-0.2842	-0.7008	-0.3741	-0.3882
Kurtosis	11.5475	17.1453	6.3912	6.8083	8.0016	6.0182	9.2631	9.6598	5.9910	8.7715	9.6874	6.0455
Jarque-Bera	2637.38*	7006.19*	420.55*	531.60*	875.38*	375.51*	1439.00*	1636.34*	312.44*	1189.06*	1526.35*	332.96*
Panel B - Unit root test (ADF)												
Return index	-1.56	-1.42	-1.39	-1.32	-1.76	-1.59	-0.65	-2.01	-1.41	-1.10	-1.78	-1.18
Log of returns	-14.56*	-28.38*	-28.95*	-26.73*	-29.71*	-27.12*	-31.28*	-28.87*	-27.31*	-14.08*	-15.73*	-27.28*
Panel C - Autocorrelation of excess returns												
AR (1)	-0.0131	0.0002	-0.0115	0.0506*	-0.0353	0.0423	-0.0954*	-0.0155	0.0427	0.0130	-0.0345	0.0632*
AR (2)	-0.0242	0.0277	-0.0378	0.0459	0.0178	0.0461	0.0573	0.0120	0.0278	-0.0213	-0.1016*	0.0105
AR (3)	0.1419*	0.0406	0.1259*	0.0753*	0.0942*	0.0263	0.1047*	0.0718*	0.1071*	0.1566*	0.1185*	0.0143*
AR (4)	-0.0187	-0.0544*	-0.0114	0.0495	-0.0307	0.0082	-0.0084	-0.0030	-0.0765*	0.0558	-0.0446*	-0.0047

Table 3.1 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Panel A - Descriptive statistics of excess returns												
Mean	0.0016	0.0031	0.0020	0.0006	0.0016	0.0004	0.0017	0.0006	0.0025	0.0008	-0.0006	0.0006
Std. Dev.	0.0363	0.0421	0.0358	0.0461	0.0552	0.0368	0.0397	0.0350	0.0386	0.0617	0.0480	0.0241
Skewness	-1.6674	-0.3590	0.0379	-0.7520	-1.0886	-1.4109	-0.6297	-0.1062	-0.2463	-0.8124	-1.1153	-0.6893
Kurtosis	17.6981	6.6571	7.3196	7.1595	13.7597	12.7833	6.7150	4.8846	6.6973	6.5562	11.9190	8.2930
Jarque-Bera	7656.96*	468.21*	629.15*	659.47*	4062.22*	2496.85*	518.68*	121.24*	468.96*	515.29*	2035.61*	1008.42*
Panel B - Unit root test (ADF)												

Return index	-1.52	-1.31	0.18	-1.75	-2.05	-1.31	-1.58	-1.34	-0.97	-1.83	-1.58	0.44
Log of returns	-30.40*	-29.21*	-29.58*	-30.81*	-9.89*	-24.27*	-30.90*	-27.93*	-29.23*	-28.24*	-24.77*	-30.38*
Panel C - Autocorrelation of excess returns												
AR (1)	-0.0629	-0.0214	-0.0148	-0.0654*	-0.0741*	-0.0192	-0.0797*	0.0189	-0.0319	0.0041	-0.0376	-0.0658*
AR (2)	0.0056	0.0032	0.0047	0.0432	-0.0554*	0.0678	-0.0092	-0.0320	0.0241	0.0296	0.0127	0.0006
AR (3)	0.1168*	0.0809*	0.0626*	0.0884*	0.1246*	0.0005	0.0641*	0.0755*	0.0672*	0.0915*	0.0396	0.0443
AR (4)	-0.0565*	-0.0830*	0.0199	-0.0560*	-0.0590*	0.0248	-0.0324	0.0042	-0.0388	-0.0093	0.0167	-0.0124

Table 3.2 Sample statistics for weekly dependent variables

All the returns are expressed in US dollars and calculated in excess of the one-month US T-bill rate. The sample covers the period January 2001 to June 2016. SMB stands for spread in returns between small and large sized firms based on market capitalization. HML stands for the spread in returns between value and growth stocks based on book-to-market values. The Jarque–Bera test for normality is based on skewness and excess kurtosis. ADF denotes Augmented Dickey-Fuller unit root test statistics. * denotes significance at a 5 per cent level.

	Descriptive statistics					Unit root test - ADF		Autocorrelation of excess returns				Correlation matrix		
	Mean	Std. Dev.	Skew-ness	Kurto-sis	Jarque-Bera	Re-turn index	Log of returns	AR (1)	AR (2)	AR (3)	AR (4)	World market returns	SMB	HML
World market returns	0.0005	0.0244	-0.8794	7.8887	909.87*	-0.56	-29.58*	-0.0376	0.0087	0.0923*	-0.0298	1		
SMB	0.0005	0.0080	-0.7647	5.9447	371.14*	-2.01	-18.17*	-0.0190	0.1047*	0.0451	-0.0032	0.0230	1	
HML	-0.0002	0.0074	0.1532	6.5103	418.54*	-2.05	-28.58*	-0.0123	0.0701*	0.0521	0.0241	0.2160	-0.0926	1

Table 3.3 summarizes the results of the International CAPM estimated by OLS and Newey-West HAC standard errors were computed (Newey & West, 1987). Recall that a necessary condition for the CAPM to hold is that the intercept term, α, must be zero. Moreover, if the international equity markets are integrated, then $\beta = 1$.

The t statistic measures the difference between the regression coefficients, $\hat{\alpha}$ and $\hat{\beta}$, and the hypothesised coefficients, α and β, divided by the standard error of the regression coefficients ($t = \frac{\hat{\beta}-\beta}{SE_{\hat{\beta}}}$). Using a 1 per cent level of significance, the critical value of the t test would be 2.57; at a 5 per cent level of significance, the critical value would be 1.96; and at a 10 per cent level of significance, the critical value would be 1.64.

The preliminary results show that the $\hat{\alpha}$s are significantly different from zero for Colombia, Czech Republic, Greece, Indonesia and Peru, which suggests that these markets do not satisfy the CAPM assumptions. Though these estimates seem very small, they are around the same level as the mean excess returns, indicating that they are economically reasonable. Second, the $\hat{\beta}$ estimates are significant at 1 per cent level and their magnitudes are economically reasonable. Previous studies found similar results, suggesting that assets in these markets may be priced locally and local factors may give better estimates for asset returns. However, in this study, we examine whether the inefficiency of the International CAPM is due to time-varying volatility in the market risk premium.

The value of $\hat{\beta}$ for Brazil, Greece, Hungary, Poland, Russia and Turkey is quite high, indicating high volatility compared to world markets, as each of these markets has experienced severe crises during the sample period. However, the value of $\hat{\beta}$ estimates for China and India imply a volatility at par suggesting a strong level of integration with world markets. A dummy variable, which takes the value of 1 for extreme negative returns in world excess returns, is incorporated into International CAPM. The dummy coefficients[55] are statistically significant at 1 per cent level for Brazil, Chile, Egypt, Hungary, Mexico, Russia, the Czech Republic, Qatar and the UAE, implying that these markets also experience negative returns. However, the dummy coefficient is positive and statistically significant for China.

[55] The coefficients of the dummy measure the average excess returns of emerging markets when the world market returns experience extreme negative returns.

To control for information processing, the International CAPM also modifies by volatility feedback. Any evidence of a negative volatility feedback effect implies a positive relationship between market volatility and the equity premium. This is the case for Brazil, China, the Czech Republic, Greece, Hungary, India, Korea, Mexico, the Philippines, Poland, South Africa, Taiwan, Thailand, and the USA (though the volatility feedback coefficient is positive and statistically significant for Egypt).

In the next phase, we check whether modifying the model using GARCH specifications alters the results. we are interested to see whether the lack of time-varying volatility in the market risk premium results in the failure of standard International CAPM. The results are presented in Table 3.4. Overall, altering the model with GARCH specifications does not necessarily change the conclusion. The $\hat{\alpha}$s remain significant for the same markets except for India, the Philippines and Qatar. In all cases, $\hat{\beta}$s remained statistically and economically significant. Under the specification of International CAPM-GARCH, the results still imply that these markets have different degrees of integration with world markets, with Colombia, Egypt, Malaysia, the Philippines, Qatar, and the UAE at the lower order of magnitude and Brazil, Greece, Hungary, Poland, Russia and Turkey at the higher order of magnitude.

To capture the time-varying volatility in the residual, the International CAPM is adjusted by the GARCH (1,1) framework in equation (3.19). The values for the sum of the estimated GARCH coefficient and the ARCH coefficient are very close to 1 in all the equity excess returns, indicating that volatility shocks are quite persistent and that the presence of at least two market phases is supported.

Table 3.3 International CAPM (OLS estimates)

The results of regression analysis where the dependent variables are weekly excess returns on MSCI indices for 23 emerging markets and the US market. The independent variable is the weekly excess returns on the world equity market. Standard errors are in parentheses. The adjusted regression model reported in equation (3.1) is adjusted for volatility feedback and a dummy is used for extreme outliers.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Parameters estimation												
Alpha	0.0008	0.0010	0.0005	0.0030	0.0021	0.0020	-0.0044	0.0009	0.0011	0.0025	0.0013	0.0008
	(0.0012)	(0.0009)	(0.0010)	(0.0013)	(0.0010)	(0.0014)	(0.0017)	(0.0013)	(0.0010)	(0.0015)	(0.0011)	(0.0008)
Beta	1.3954	0.8128	1.1110	0.7879	0.9348	0.5733	1.3573	1.3040	1.0016	0.8626	1.1617	0.5512
	(0.0446)	(0.0256)	(0.0363)	(0.0462)	(0.0380)	(0.0524)	(0.0740)	(0.0454)	(0.0366)	(0.0435)	(0.0368)	(0.0259)
feedback	-0.1352	0.0388	-0.1246	0.0280	-0.0550	-0.0137	-0.1592	-0.1156	-0.0784	-0.0311	-0.1417	0.0256
	(0.0446)	(0.0260)	(0.0245)	(0.0239)	(0.0285)	(0.0318)	(0.0219)	(0.0220)	(0.0309)	(0.0253)	(0.0151)	(0.0246)
dummy	-0.0547	-0.0497	0.0498	0.0125	-0.0454	-0.0477	0.0418	-0.0976	0.0173	-0.0241	-0.0136	0.0136
	(0.0106)	(0.0054)	(0.0115)	(0.0210)	(0.0381)	(0.0156)	(0.0480)	(0.0159)	(0.0260)	(0.0197)	(0.0151)	(0.0192)

Table 3.3 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Parameters estimation												
Alpha	0.0011	0.0026	0.0016	-0.0002	0.0014	0.0005	0.0010	0.0001	0.0020	0.0002	-0.0004	0.0002
	(0.0007)	(0.0012)	(0.0011)	(0.0010)	(0.0014)	(0.0015)	(0.0009)	(0.0009)	(0.0011)	(0.0018)	(0.0020)	(0.0003)
Beta	1.1396	1.0383	0.7119	1.2851	1.3528	0.4919	1.1995	0.9168	0.8442	1.3575	0.6105	0.9086
	(0.0262)	(0.0384)	(0.0394)	(0.0379)	(0.0452)	(0.0557)	(0.0321)	(0.0358)	(0.0450)	(0.0591)	(0.0710)	(0.0088)
feedback	-0.1462	-0.0198	-0.1051	-0.1558	-0.0820	-0.0246	-0.1246	-0.0604	-0.0958	-0.0303	-0.0120	-0.1786
	(0.0297)	(0.0319)	(0.0246)	(0.0269)	(0.0240)	(0.0311)	(0.0295)	(0.0250)	(0.0234)	(0.0273)	(0.0261)	(0.0247)
dummy	-0.0362	-0.0138	0.0205	-0.0003	-0.1481	-0.0863	0.0073	0.0250	0.0032	-0.0397	-0.1334	-0.0117
	(0.0055)	(0.0133)	(0.0397)	(0.0141)	(0.0138)	(0.0107)	(0.0204)	(0.0678)	(0.0149)	(0.0593)	(0.0140)	(0.0070)

Table 3.4 International CAPM-GARCH (1,1)

The result of regression analysis where the dependent variables are weekly excess returns on MSCI indices for 23 emerging markets and the US market. The independent variable is the weekly excess returns on world equity market. Standard errors are in parentheses. The adjusted regression model reported in equation (3.1) is adjusted for volatility feedback, a dummy is used for extreme outliers, and the conditional variance is given by equation (3.2).

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
International CAPM-GARCH estimation												
Alpha	0.0001	0.0009	0.0004	0.0025	0.0019	0.0033	0.0005	0.0017	0.0022	0.0027	0.0007	0.0012
	(0.0009)	(0.0008)	(0.0008)	(0.0010)	(0.0009)	(0.0011)	(0.0010)	(0.0010)	(0.0009)	(0.0010)	(0.0008)	(0.0006)
Beta	1.4649	0.8508	0.9894	0.7113	0.8771	0.5048	1.1824	1.2335	0.9127	0.8569	1.1201	0.5218
	(0.0426)	(0.0316)	(0.0384)	(0.0408)	(0.0418)	(0.0505)	(0.0509)	(0.0483)	(0.0407)	(0.0472)	(0.0422)	(0.0260)
feedback	0.0017	0.0699	-0.0732	0.0572	-0.0352	-0.0224	-0.1026	-0.1042	-0.0498	-0.0390	-0.1319	0.0548
	(0.0339)	(0.0364)	(0.0371)	(0.0358)	(0.0355)	(0.0331)	(0.0342)	(0.0344)	(0.0356)	(0.0320)	(0.0357)	(0.0325)
dummy	0.0103	-0.0312	0.0023	0.0212	-0.0475	-0.0135	0.0050	-0.0736	0.0159	0.0207	-0.0110	-0.0017
	(0.0135)	(0.0097)	(0.0360)	(0.0154)	(0.0218)	(0.0217)	(0.0266)	(0.0296)	(0.0217)	(0.0221)	(0.0149)	(0.0113)
C	0.0000	0.0000	0.0000	0.0001	0.0001	0.0001	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RESID(-1)^2	0.1137	0.0862	0.1385	0.1352	0.0516	0.0662	0.0642	0.0838	0.0718	0.0665	0.1319	0.0788
	(0.0334)	(0.0274)	(0.0330)	(0.0347)	(0.0220)	(0.0268)	(0.0162)	(0.0268)	(0.0232)	(0.0162)	(0.0256)	(0.0241)
GARCH(-1)	0.8677	0.8708	0.8189	0.8248	0.8870	0.8642	0.9403	0.7819	0.8870	0.9128	0.8206	0.8967
	(0.0348)	(0.0376)	(0.0381)	(0.0373)	(0.0510)	(0.0534)	(0.0150)	(0.0678)	(0.0363)	(0.0186)	(0.0308)	(0.0281)

Table 3.4 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
International CAPM-GARCH estimation												
Alpha	0.0009	0.0022	0.0024	0.0000	0.0002	0.0015	0.0005	0.0002	0.0017	0.0013	0.0009	0.0002
	(0.0006)	(0.0011)	(0.0007)	(0.0009)	(0.0010)	(0.0008)	(0.0008)	(0.0007)	(0.0009)	(0.0014)	(0.0013)	(0.0002)
Beta	1.1120	0.9728	0.7277	1.2645	1.3298	0.2850	1.2253	0.9180	0.8083	1.2731	0.5376	0.9008
	(0.0300)	(0.0476)	(0.0380)	(0.0425)	(0.0505)	(0.0345)	(0.0374)	(0.0357)	(0.0448)	(0.0623)	(0.0562)	(0.0111)

feedback	-0.0959	0.0104	-0.1352	-0.1055	-0.0298	0.1060	-0.0869	-0.0705	-0.0722	-0.0351	0.0740	-0.1835
	(0.0361)	(0.0377)	(0.0338)	(0.0369)	(0.0366)	(0.0401)	(0.0383)	(0.0352)	(0.0357)	(0.0353)	(0.0450)	(0.0362)
dummy	-0.0012	-0.0084	0.0285	-0.0456	-0.0814	-0.0018	0.0206	0.0213	0.0116	-0.0618	-0.0162	-0.0164
	(0.0106)	(0.0180)	(0.0258)	(0.0129)	(0.0294)	(0.0153)	(0.0160)	(0.0315)	(0.0175)	(0.0317)	(0.0219)	(0.0069)
C	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RESID(-1)^2	0.0657	0.0871	0.0765	0.1024	0.1208	0.1338	0.0536	0.0598	0.0907	0.0425	0.2399	0.1075
	(0.0207)	(0.0256)	(0.0227)	(0.0259)	(0.0262)	(0.0368)	(0.0204)	(0.0165)	(0.0284)	(0.0142)	(0.0511)	(0.0275)
GARCH(-1)	0.9063	0.8764	0.8925	0.8495	0.8483	0.8697	0.9127	0.9263	0.8636	0.9375	0.7048	0.8499
	(0.0307)	(0.0347)	(0.0252)	(0.0332)	(0.0283)	(0.0286)	(0.0308)	(0.0181)	(0.0373)	(0.0160)	(0.0501)	(0.0363)

3.4.2 State-dependent Volatility and the Estimated Market Risk Premium

To investigate an adequate number of states and capture the shifting behaviour in return volatility, this chapter tests the two-state model against the three-state model of market excess returns. The test of volatility feedback in the three-state model adds complexity to the estimation of parameters but does not yield commensurate model fitness. The parameter estimation for the three-state model shows that the high volatility state only captures extreme negative shocks rather than volatility persistence. This finding is in line with Hamilton and Susmel (1994) that "extremely large shocks arise from quite different causes and have different consequences for subsequent volatility than do small shocks" To account for negative outliers and following Abdymomunov and Morley (2011), we test the model in equation (3.12) with a dummy variable to capture the extreme outliers in excess returns. The model for the world return is defined as follows:

$$r_{m,t} = E[r_{m,t}|S_{m,t-1}] + f_{m,t} + \gamma D_t + \varepsilon_{m,t} \qquad (3.23)$$

Where μ_{m,s_t} is the state-dependent mean (expected returns), D_t is the dummy variable that is equal to one for two extreme negative observations and zero elsewhere and σ^2_{i,s_t} is conditional variance, as per Abdymomunov and Morley (2011). We observe that a model with only a few negative observations in the sample period improves the log likelihood value compared to a three-state model and provides a better explanation of the data.[56] It should also be noted that the dummy variable is only incorporated into the world market returns process, while the SD International CAPM maintains the same form as indicated in equation (3.18), and the parameters in the SD International CAPM rely on the entire sample set including extreme negative returns. Further to state-dependent market volatility, we also account for heteroskedasticity in the residual, considering that idiosyncratic news, σ^2_{i,s_t}, follows a two-state Markov-switching model for the world return volatility. The estimation is based on Hamilton (1994).

[56] We also include a dummy in the model with all the recessions reported by the NBER, but the model with a dummy for extreme negative outliers produces a much better likelihood value.

Table 3.5 State-dependent parameters estimate for volatility and market risk premium

The world markets return expressed in equation (3.11), where δ denotes for volatility feedback in equation (3.17) and γ denotes a dummy variable for extreme outliers in equation (3.23). Standard errors are in parenthesis. Log L stands for log likelihood. Model 1 is the model with volatility feedback and dummy, Model 2 is the model with volatility feedback and Model 3 is the model with volatility feedback and dummy.

Model	μ_1	μ_2	δ	γ	σ_1	σ_2	p_{11}	p_{22}	$h_{0:}\,\mu_1 = \mu_2$	$h_{0:}\,\sigma_1 = \sigma_2$	log L
Model 1	0.0034	-0.0046			0.0144	0.0359					
	(0.0008)	(0.0022)			(0.0002)	(0.0006)	0.9581	0.9249	0.0008	0.0000	1961.1950
Model 2	0.0035	-0.0048	-0.0646		0.0144	0.0359					
	(0.0007)	(0.0021)	(0.0371)		(0.0002)	(0.0006)	0.9583	0.9242	0.0003	0.0000	1960.2380
Model 3	0.0038	-0.0026	-0.0737	-0.1341	0.0136	0.0314					
	(0.0007)	(0.0017)	(0.0363)	(0.0181)	(0.0002)	(0.0004)	0.9538	0.9385	0.0009	0.0000	1984.5740

Table 3.5 reports the results for state-dependent market volatility and market risk premium as specified in equation (3.23). In this regard, comparison results summarize the restrictions of the model both with and without dummies for extreme negative returns. In terms of the volatility in the two-state model, the continuation probabilities indicate that both states are persistent with 95 per cent and 94 per cent week-to-week probabilities of staying in low volatility and high volatility states respectively. The estimated persistence for state i is $\frac{1}{1-p_{ii}}$ for $i = 1, 2$. State 1 has an estimated persistence of 21 weeks and state 2 has an estimated persistence of 16 weeks for the model with the dummy for extreme negative returns. Figure 3.2 depicts the two-state transition probabilities. The transition probabilities are quite high, indicating that both states are persistent. This can be described as a momentum effect because the process is more likely to remain in the same state than to switch to another state.

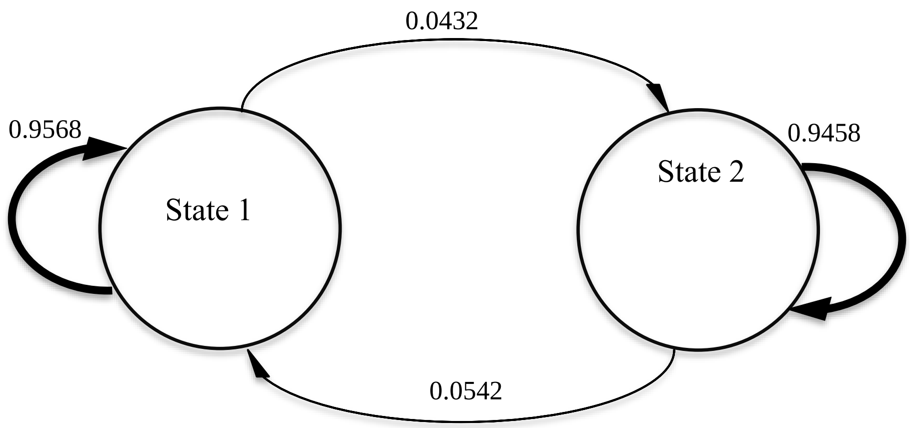


Figure 3.2 Two-state transition diagram

This Figure shows that the transition probabilities are quite high in both states, indicating that both states are persistent.

Figure 3.3 shows the volatility clustering in world market returns in Panel A and the smoothed probabilities of the low volatility state during the sample period in Panel B. It is apparent that the high volatility state observed for all of the National Bureau of Economic Research (NBER) recessions implies a link between market volatility and economic cycles.

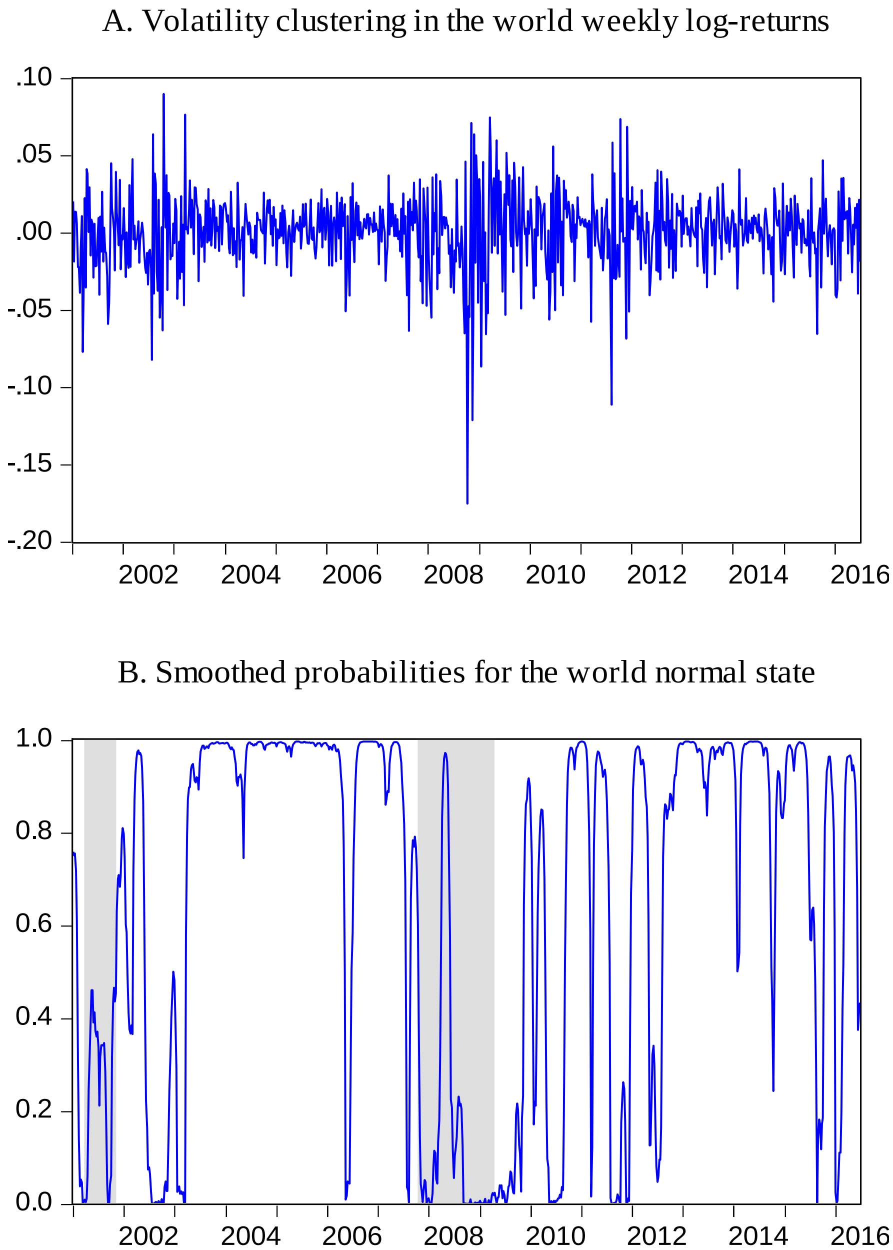


Figure 3.3 Volatility clustering in the world weekly returns and smoothed probabilities

In Panel A, returns are calculated as logarithmic returns in excess of the one-month US T-bill rate. Panel B displays the smoothed probabilities for the world normal state. The shaded bars show NBER recessions.

3.4.3 State-dependent International CAPM

Table 3.6 contains the estimates for the SD International CAPM defined in equation (3.18) for 23 emerging markets and the US market. First, the $\hat{\alpha}$s are not significantly different from zero at conventional levels of significance, which appears consistent with the theory of CAPM. The exceptions are Colombia, Czech Republic, Egypt, Hungary, India, Indonesia and Peru in state 1, and Greece in states 1 and 2, where we obtain significant intercepts. Second, we test whether there is any pattern, indicated by changes in betas, associated with high or low-risk states. The results, however, do not imply any clear pattern for this assumption. More precisely, betas are not necessarily lower in low volatility states and higher in high volatility states. There is no evidence that the data are inconsistent with the CAPM in either of the states. The estimated $\hat{\beta}$s have diverse values across the two market volatility states. Betas for some of these markets in the low volatility state are higher than for those in the high volatility state. This is inconsistent with the theoretical assumption about volatility behaviour, which states that financial markets are more correlated to each other in bad times (Junior & Franca, 2012; Longin & Solnik, 2001). Different correlation levels will result in inconsistency of asset returns, leading to poor estimates about portfolio performance when markets decline. The inconsistency in results might reflect the fact that the unconditional CAPM may only reflect a partial property of the return series.

Taking a different perspective, we obtain a low value of $\hat{\beta}$ coefficients for Egypt, the Philippines, Malaysia, and Qatar, implying less volatility relative to the world equity markets. For example, $\hat{\beta}$ coefficients for Malaysia are 0.54 and 0.55 for state 1 and state 2 respectively, with standard deviations of 0.01 and 0.03 (i.e., exponential (-4.32) and exponential (-3.57)) for state 1 and state 2 respectively. These findings may reflect the fact that assets in these markets may be priced locally and the risks may come from local factors, such as economic factors or idiosyncratic volatility. In other words, these markets expose time-varying market volatility despite having less investment restriction (e.g. Malaysia, the Philippines, Qatar and the UAE), which may enhance international investment. In comparison, $\hat{\beta}$ coefficients for Poland, Russia and Turkey are 1.23, 1.27 and 1.32 (with the value of standard deviation 0.03) in state 1 and 1.28, 1.46 and 1.374 (with the values of standard deviation 0.07, 0.09 and 0.08) in state 2 implying less volatility relative to world equity markets.

Moreover, we find significant results for state-dependent beta coefficients. This evidence implies that the estimated beta from the unconditional International CAPM underestimates the risk premium in the high volatility state while overestimating the risk premium in the low volatility state. In comparison, the SD International CAPM can allow the market risk, beta, to be drawn from two different states to characterize the instability of beta that was found in previous studies.

Table 3.6 Estimates of the SD International CAPM for emerging markets indices

The results of regression analysis where the dependent variables are weekly returns on MSCI indices for 23 emerging markets and the US market. The independent variable is the weekly return on the world equity market in excess of the one-month T-bill rate. Panels A and B report alphas and betas conditional on smoothed probabilities of the high market volatility state being lower (higher) than 0.5 from the state-dependent International CAPM described by equations (3.17) and (3.18), modified with a dummy in equation (3.23). Standard errors are in parentheses.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Panel A - State-dependent alphas												
Alpha 1	0.0000	0.0004	0.0006	0.0038	0.0025	0.0072	0.0021	0.0019	0.0032	0.0039	0.0003	0.0009
	(0.0011)	(0.0009)	(0.0008)	(0.0013)	(0.0010)	(0.0016)	(0.0012)	(0.0012)	(0.0013)	(0.0013)	(0.0008)	(0.0009)
Alpha 2	0.0019	0.0020	0.0015	0.0019	0.0014	-0.0065	-0.0128	-0.0069	-0.0022	-0.0015	0.0065	0.0011
	(0.0056)	(0.0026)	(0.0022)	(0.0040)	(0.0050)	(0.0044)	(0.0034)	(0.0078)	(0.0026)	(0.0059)	(0.0047)	(0.0018)
Panel B - State-dependent betas												
Beta 1	1.6029	0.9212	0.8519	0.5810	0.7461	0.4588	1.0584	1.1968	0.6152	0.8633	1.1532	0.5455
	(0.0575)	(0.0495)	(0.0472)	(0.0683)	(0.0573)	(0.0794)	(0.0626)	(0.0743)	(0.1008)	(0.0705)	(0.0476)	(0.0459)
Beta 2	0.6868	0.6996	1.4011	1.2180	1.2928	0.7483	1.7220	1.6622	1.3940	0.9373	1.1907	0.5516
	(0.1995)	(0.0871)	(0.1026)	(0.2212)	(0.1417)	(0.1350)	(0.1643)	(0.2982)	(0.1052)	(0.1730)	(0.1418)	(0.0563)
Panel C - Other parameters												
Log (Sigma 1)	-3.6832	-4.0508	-3.9365	-3.7572	-3.6977	-3.7395	-3.6145	-3.4954	-3.7572	-3.6079	-3.7603	-4.3278
	(0.0407)	(0.0568)	(0.0378)	(0.0665)	(0.0359)	(0.0721)	(0.0464)	(0.0415)	(0.0489)	(0.0482)	(0.0372)	(0.0841)
Log (Sigma 2)	-2.8357	-3.3916	-3.1841	-2.9950	-3.0658	-2.8752	-2.7074	-2.6425	-3.2603	-2.6965	-2.8238	-3.5743
	(0.0793)	(0.0685)	(0.0445)	(0.0881)	(0.1023)	(0.0653)	(0.0443)	(0.1437)	(0.0740)	(0.1057)	(0.0696)	(0.0813)
feedback	0.0218	0.0710	-0.1075	0.0496	-0.0194	-0.0362	-0.1197	-0.1091	-0.0402	-0.0580	-0.1638	0.0485
	(0.0377)	(0.0365)	(0.0366)	(0.0392)	(0.0376)	(0.0355)	(0.0376)	(0.0382)	(0.0387)	(0.0370)	(0.0375)	(0.0382)
dummy	-0.1413	-0.0679	0.0870	0.0146	-0.0343	-0.0215	0.1019	-0.0726	0.0738	0.0067	-0.0248	0.0071
	(0.0246)	(0.0232)	(0.0281)	(0.0179)	(0.0237)	(0.0202)	(0.0461)	(0.0248)	(0.0320)	(0.0256)	(0.0213)	(0.0130)

Table 3.6 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA

Panel A - State-dependent alphas												
Alpha 1	0.0013	0.0028	0.0029	0.0001	0.0029	0.0017	0.0011	0.0004	0.0018	0.0006	0.0020	0.0003
	(0.0007)	(0.0015)	(0.0011)	(0.0009)	(0.0014)	(0.0010)	(0.0008)	(0.0009)	(0.0010)	(0.0015)	(0.0015)	(0.0002)
Alpha 2	0.0015	0.0021	-0.0008	-0.0023	0.0023	-0.0018	-0.0098	0.0008	0.0032	-0.0005	-0.0126	0.0001
	(0.0073)	(0.0017)	(0.0026)	(0.0069)	(0.0041)	(0.0035)	(0.0325)	(0.0028)	(0.0031)	(0.0057)	(0.0088)	(0.0009)
Panel B - State-dependent betas												
Beta 1	1.0879	0.3532	0.7111	1.2394	1.2762	0.2519	1.1790	0.9196	0.7737	1.3288	0.5180	0.8856
	(0.0409)	(0.0717)	(0.0867)	(0.0565)	(0.0991)	(0.0465)	(0.0412)	(0.0533)	(0.0541)	(0.0762)	(0.0677)	(0.0178)
Beta 2	1.5449	1.4461	0.7116	1.2823	1.4620	0.8367	1.6235	0.8064	0.9647	1.3454	1.0300	0.9271
	(0.2237)	(0.0762)	(0.1043)	(0.2245)	(0.1325)	(0.1233)	(0.8280)	(0.0929)	(0.1294)	(0.1922)	(0.2239)	(0.0294)
Panel C -Other parameters												
Log (Sigma 1)	-3.9509	-3.7586	-3.9029	-3.6412	-3.7054	-4.1190	-3.6884	-3.8498	-3.7726	-3.2814	-3.5706	-5.0361
	(0.0465)	(0.0442)	(0.0837)	(0.0368)	(0.0631)	(0.0689)	(0.0286)	(0.0384)	(0.0397)	(0.0323)	(0.0611)	(0.0350)
Log (Sigma 2)	-3.1522	-3.3380	-3.1144	-2.7066	-2.8026	-3.0217	-2.4547	-3.2164	-3.0316	-2.5178	-2.5359	-4.3353
	(0.1893)	(0.0362)	(0.1195)	(0.1146)	(0.0728)	(0.0630)	(0.3397)	(0.0565)	(0.0587)	(0.0572)	(0.0957)	(0.0925)
feedback	-0.1155	0.0008	-0.1098	-0.1133	-0.0286	0.0208	-0.0804	-0.0373	-0.0821	-0.0297	0.0687	-0.2010
	(0.0369)	(0.0361)	(0.0420)	(0.0368)	(0.0426)	(0.0439)	(0.0349)	(0.0395)	(0.0373)	(0.0359)	(0.0469)	(0.0356)
dummy	0.0083	0.0421	0.0234	-0.0261	-0.1059	-0.0184	0.0024	0.0230	0.0079	-0.0613	-0.0273	-0.0130
	(0.0153)	(0.0231)	(0.0178)	(0.0222)	(0.0235)	(0.0160)	(0.0160)	(0.0183)	(0.0210)	(0.0333)	(0.0274)	(0.0062)

Dummy coefficients are negative and statistically significant at the 1 per cent level for Brazil, Chile, Hungary, Russia and Turkey, implying that these markets also experience negative returns. But dummy coefficients are positive and statistically significant at the 1 per cent level for China, Greece, India and Peru. Additionally, the volatility feedback coefficients are negative and statistically significant at the 1 per cent level for China, Greece, Hungary, Korea, Mexico, the Philippines, Poland, South Africa, Thailand and the USA, implying that there is a positive relationship between equity market volatility and the equity risk premium. However, the volatility feedback coefficients are positive and statistically significant for Chile.

3.4.4 State-dependent International Three-factor Model

Table 3.7 summarizes the model in equation (3.19). First, we observe that alpha is significantly different from zero only for Greece. Second, the variation in beta estimates is almost identical to those achieved by the unconditional International CAPM. Third, the size risk factor coefficients are at a significant level for most of the equity portfolio except for the Czech Republic, Greece, Hungary, Poland, Qatar and the UAE. On the other hand, we only achieve the level of significance for value risk premiums for China, Qatar and Turkey. Consistent with the previous studies (Bruner et al., 2008; Cakici et al., 2013), this result indicates that global size and value factors may not contain useful information about asset pricing returns in emerging markets. In contrast to the unconditional CAPM, the average power of the R-squared statistic marginally increases from 0.37 to 0.39 for the three-factor model. However, we am interested in testing whether this is caused by time-varying market volatility.

Table 3.8 summarizes the results of the state-dependent three-factor model defined in equation (3.22). We find that the size and value effect estimates are different depending on the market volatility state. These results run contrary to what were achieved by the single-state three-factor model and may partially explain the failure of the global risk factors to explain asset pricing returns in emerging markets.

Table 3.7 Fama and French three-factor model

The results of regression analysis where the dependent variables are weekly excess returns on MSCI indices for 23 emerging markets and the US market. The independent variables are the weekly excess returns on the world equity market, and value and size factors in excess of the one-month T-bill rate. Standard errors are in parentheses. The adjusted regression model is reported in equation (3.19).

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
International CAPM-OLS estimation												
Alpha	0.0005	0.0007	0.0002	0.0027	0.0020	0.0016	-0.0045	0.0009	0.0006	0.0018	0.0007	0.0005
	(0.0012)	(0.0009)	(0.0010)	(0.0013)	(0.0010)	(0.0014)	(0.0017)	(0.0013)	(0.0010)	(0.0014)	(0.0010)	(0.0008)
Beta	1.4027	0.8332	1.1274	0.7751	0.9275	0.5671	1.3260	1.2797	0.9883	0.8753	1.1770	0.5533
	(0.0496)	(0.0275)	(0.0376)	(0.0510)	(0.0401)	(0.0555)	(0.0751)	(0.0484)	(0.0397)	(0.0463)	(0.0376)	(0.0262)
SMB	0.5012	0.3420	0.3919	0.5825	0.1296	0.8223	0.4502	0.1571	0.8531	1.3012	0.7963	0.4837
	(0.1188)	(0.0981)	(0.0995)	(0.1360)	(0.1211)	(0.1544)	(0.2519)	(0.1283)	(0.1002)	(0.1125)	(0.1026)	(0.0634)
HML	-0.1896	-0.2403	-0.2698	0.2443	0.1100	0.1953	0.4331	0.3782	0.1303	-0.1142	-0.2301	0.0293
	(0.1443)	(0.1048)	(0.1189)	(0.1669)	(0.1225)	(0.1833)	(0.2577)	(0.1757)	(0.1157)	(0.1584)	(0.1191)	(0.0776)
feedback	-0.1225	0.0241	-0.1249	0.0212	-0.0587	-0.0286	-0.1638	-0.1229	-0.0628	-0.0449	-0.1633	0.0133
	(0.0206)	(0.0267)	(0.0263)	(0.0243)	(0.0284)	(0.0325)	(0.0223)	(0.0235)	(0.0310)	(0.0284)	(0.0184)	(0.0261)
dummy	-0.0473	-0.0424	0.0572	0.0194	-0.0442	-0.0367	0.0448	-0.0978	0.0282	-0.0044	0.0018	0.0209
	(0.0120)	(0.0059)	(0.0127)	(0.0238)	(0.0383)	(0.0169)	(0.0434)	(0.0155)	(0.0288)	(0.0223)	(0.0185)	(0.0145)

Table 3.7 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
International CAPM-OLS estimation												
Alpha	0.0009	0.0020	0.0011	-0.0002	0.0012	0.0008	0.0008	-0.0003	0.0014	-0.0002	-0.0001	0.0002
	(0.0007)	(0.0012)	(0.0010)	(0.0010)	(0.0014)	(0.0015)	(0.0009)	(0.0009)	(0.0010)	(0.0018)	(0.0021)	(0.0003)
Beta	1.1377	1.0493	0.7127	1.2711	1.3439	0.4580	1.1974	0.9258	0.8488	1.3959	0.5931	0.9120
	(0.0279)	(0.0413)	(0.0420)	(0.0417)	(0.0507)	(0.0588)	(0.0338)	(0.0369)	(0.0460)	(0.0643)	(0.0767)	(0.0092)
SMB	0.4266	1.0239	0.7357	0.1897	0.4793	-0.0730	0.3591	0.5750	0.9505	0.4869	-0.3353	-0.0521
	(0.0771)	(0.1297)	(0.1004)	(0.1217)	(0.1414)	(0.1038)	(0.0910)	(0.0931)	(0.0978)	(0.1832)	(0.1979)	(0.0264)

HML	-0.0019	-0.0850	-0.0261	0.1991	0.1203	0.5134	0.0101	-0.0951	-0.0351	-0.5175	0.4986	-0.0472
	(0.0893)	(0.1260)	(0.1130)	(0.1208)	(0.1483)	(0.1919)	(0.1183)	(0.0980)	(0.1368)	(0.2005)	(0.2639)	(0.0313)
feedback	-0.1537	0.0052	-0.1126	-0.1604	-0.0835	-0.0145	-0.1337	-0.0765	-0.1241	-0.0367	-0.0034	-0.1799
	(0.0295)	(0.0319)	(0.0262)	(0.0264)	(0.0241)	(0.0319)	(0.0308)	(0.0271)	(0.0258)	(0.0279)	(0.0270)	(0.0254)
dummy	-0.0297	0.0010	0.0316	0.0010	-0.1421	-0.0909	0.0127	0.0342	0.0190	-0.0293	-0.1392	-0.0121
	(0.0059)	(0.0141)	(0.0740)	(0.0149)	(0.0151)	(0.0108)	(0.0240)	(0.0351)	(0.0182)	(0.0553)	(0.0144)	(0.0069)

Table 3.8 Estimates of the state-dependent three factor model for emerging markets indices

The results of regression analysis where the dependent variables are weekly returns on MSCI indices for 23 emerging markets and the US market. The independent variables are the weekly return on the world equity market, and value and size factors in excess of the one-month T-bill rate. Panels A, B and C report alphas, betas, size and value conditional on smoothed probabilities of the high market volatility state being lower (higher) than 0.5 from the state-dependent three factor model described by equations (3.17) and (3.22). Standard errors are in parentheses.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Panel A - State-dependent alphas												
Alpha 1	0.0005	0.0008	0.0004	0.0035	0.0023	0.0071	0.0017	0.0017	0.0015	0.0033	-0.0001	0.0009
	(0.0011)	(0.0009)	(0.0008)	(0.0013)	(0.0010)	(0.0017)	(0.0012)	(0.0012)	(0.0011)	(0.0012)	(0.0008)	(0.0008)
Alpha 2	0.0001	-0.0007	0.0013	0.0019	0.0022	-0.0055	-0.0123	-0.0043	-0.0019	-0.0009	0.0054	0.0008
	(0.0051)	(0.0028)	(0.0023)	(0.0040)	(0.0048)	(0.0038)	(0.0034)	(0.0061)	(0.0038)	(0.0042)	(0.0044)	(0.0016)
Panel B - State-dependent betas												
Beta 1	1.5320	0.8078	0.8600	0.5630	0.7290	0.4323	1.0679	1.1688	0.7881	0.8815	1.1546	0.5085
	(0.0584)	(0.0427)	(0.0485)	(0.0562)	(0.0566)	(0.0863)	(0.0657)	(0.0697)	(0.0608)	(0.0776)	(0.0480)	(0.0403)
Beta 2	1.4296	1.0144	1.3914	1.2512	1.3504	0.7299	1.6938	1.7306	1.2742	1.0274	1.2840	0.5946
	(0.1675)	(0.0916)	(0.0998)	(0.1931)	(0.1476)	(0.1251)	(0.1700)	(0.2513)	(0.1102)	(0.1454)	(0.1453)	(0.0574)
Panel C - State-dependent FF factors												
SMB 1	-0.0837	0.2191	0.3024	0.5115	0.2542	0.0567	0.5146	0.6126	0.7027	0.0564	0.3780	0.2735
	(0.1913)	(0.1212)	(0.1275)	(0.1607)	(0.1564)	(0.2302)	(0.1600)	(0.1895)	(0.1437)	(0.1959)	(0.1381)	(0.1174)
SMB 2	1.8724	0.5395	0.5215	0.5776	-0.3660	1.5946	0.1696	-1.6217	0.9385	3.0993	1.5129	0.6582
	(0.6542)	(0.2634)	(0.2782)	(0.5048)	(0.4484)	(0.3943)	(0.5234)	(0.7715)	(0.3588)	(0.4861)	(0.4512)	(0.1707)
HML 1	0.1431	0.2473	0.0100	0.2732	0.2383	0.0227	0.0363	0.4124	-0.4075	-0.2272	-0.3499	0.1573

	(0.1942)	(0.1259)	(0.1752)	(0.1974)	(0.1927)	(0.2183)	(0.1779)	(0.2083)	(0.1805)	(0.2570)	(0.1650)	(0.1690)
HML 2	-0.6367	-1.2871	-0.2691	0.0842	-0.4442	0.4601	1.5084	-0.0460	0.9383	-0.2509	-0.2853	-0.0362
	(0.5087)	(0.4610)	(0.2698)	(0.6827)	(0.4547)	(0.4778)	(0.5858)	(0.7200)	(0.3561)	(0.4620)	(0.3941)	(0.1692)
Panel D - other parameters												
Log (Sigma 1)	-3.6922	-4.0418	-3.9362	-3.7695	-3.6947	-3.7579	-3.6374	-3.5197	-3.7130	-3.6167	-3.7641	-4.3486
	(0.0410)	(0.0432)	(0.0370)	(0.0568)	(0.0369)	(0.0740)	(0.0451)	(0.0441)	(0.0413)	(0.0466)	(0.0328)	(0.0598)
Log (Sigma 2)	-2.8397	-3.3868	-3.1878	-2.9988	-3.0980	-2.9368	-2.7169	-2.7514	-3.1768	-2.8874	-2.8627	-3.6183
	(0.0836)	(0.0693)	(0.0449)	(0.0776)	(0.0999)	(0.0639)	(0.0459)	(0.1293)	(0.0833)	(0.0658)	(0.0664)	(0.0549)
feedback	-0.0050	0.0484	-0.1024	0.0481	-0.0262	-0.0457	-0.1173	-0.1199	-0.0028	-0.0620	-0.1775	0.0399
	(0.0376)	(0.0376)	(0.0368)	(0.0394)	(0.0384)	(0.0368)	(0.0377)	(0.0414)	(0.0381)	(0.0374)	(0.0366)	(0.0378)
dummy	-0.1033	-0.0059	-0.1145	-0.1090	-0.0389	0.0279	-0.0896	-0.0794	-0.1091	-0.0508	0.0622	-0.1990
	(0.0186)	(0.0165)	(0.0281)	(0.0176)	(0.0228)	(0.0208)	(0.0541)	(0.0252)	(0.0207)	(0.0244)	(0.0214)	(0.0137)

Table 3.8 continued

	Mexico	Peru	Philip-pines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Panel A - State-dependent alphas												
Alpha 1	0.0027	0.0018	0.0023	-0.0008	0.0018	0.0017	-0.0188	-0.0002	0.0015	0.0011	0.0020	0.0002
	(0.0010)	(0.0014)	(0.0011)	(0.0010)	(0.0013)	(0.0010)	(0.0063)	(0.0008)	(0.0010)	(0.0015)	(0.0015)	(0.0002)
Alpha 2	-0.0038	0.0017	-0.0023	-0.0029	0.0007	-0.0014	0.0010	-0.0002	0.0015	-0.0026	-0.0080	-0.0001
	(0.0027)	(0.0017)	(0.0043)	(0.0066)	(0.0042)	(0.0033)	(0.0009)	(0.0024)	(0.0029)	(0.0057)	(0.0075)	(0.0012)
Panel B - State-dependent betas												
Beta 1	0.9662	0.4884	0.6726	1.2703	1.3058	0.2471	3.3313	0.8985	0.7762	1.3212	0.5565	0.9271
	(0.0571)	(0.0688)	(0.0685)	(0.0598)	(0.0783)	(0.0460)	(0.2032)	(0.0463)	(0.0513)	(0.0772)	(0.0707)	(0.0164)
Beta 2	1.5160	1.4647	0.9032	1.3534	1.5229	0.7805	1.1349	0.9608	0.9736	1.7049	0.5684	0.8656
	(0.1447)	(0.0812)	(0.2024)	(0.2312)	(0.1419)	(0.1284)	(0.0430)	(0.0850)	(0.1174)	(0.2217)	(0.2636)	(0.0415)
Panel C - State-dependent FF factors												
SMB 1	-0.1772	0.9210	0.2810	0.3788	0.2435	0.1562	-2.0383	0.3030	0.5510	-0.0656	-0.0754	-0.0761
	(0.2496)	(0.1719)	(0.1676)	(0.1615)	(0.2267)	(0.1849)	(0.3094)	(0.1419)	(0.1454)	(0.2489)	(0.2331)	(0.0451)
SMB 2	1.8036	0.3698	1.7844	0.3158	0.9348	-0.2892	0.4771	0.7660	1.5512	1.7986	-0.7767	0.0064
	(0.3481)	(0.2302)	(0.7213)	(0.6248)	(0.4084)	(0.3907)	(0.1200)	(0.2400)	(0.3467)	(0.5887)	(0.7178)	(0.1421)
HML 1	-0.1544	0.1338	0.3082	0.2268	0.6592	0.1079	-4.6204	-0.3998	-0.1020	0.4025	0.2602	-0.2207
	(0.2199)	(0.1731)	(0.2248)	(0.1778)	(0.2645)	(0.1831)	(0.6949)	(0.1975)	(0.1775)	(0.2591)	(0.2582)	(0.0506)

HML 2	-0.0326	-0.4975	-0.9883	0.0029	-0.2912	0.5775	0.1045	-0.0167	0.0857	-2.1621	0.9404	0.2588
	(0.4813)	(0.2505)	(0.9886)	(0.7055)	(0.4022)	(0.4353)	(0.1273)	(0.2400)	(0.3520)	(0.6301)	(0.8073)	(0.1410)
Panel D - other parameters												
Log (Sigma 1)	-4.0284	-3.8045	-3.8285	-3.6471	-3.6407	-4.1517	-4.4141	-3.9758	-3.7804	-3.2703	-3.6135	-5.0425
	(0.0493)	(0.0457)	(0.0983)	(0.0410)	(0.0495)	(0.0778)	(0.3699)	(0.0328)	(0.0370)	(0.0310)	(0.0604)	(0.0360)
Log (Sigma 2)	-3.7708	-3.3403	-3.0266	-2.7443	-2.7876	-3.0473	-3.6925	-3.2342	-3.0797	-2.5588	-2.6029	-4.2688
	(0.1099)	(0.0363)	(0.1372)	(0.1147)	(0.0704)	(0.0651)	(0.0265)	(0.0493)	(0.0570)	(0.0583)	(0.0824)	(0.1072)
feedback	0.0133	-0.0020	0.0920	0.0183	-0.0288	-0.0186	0.1012	-0.0614	0.0424	0.0205	-0.0115	0.0146
	(0.0409)	(0.0373)	(0.0412)	(0.0371)	(0.0388)	(0.0446)	(0.0375)	(0.0366)	(0.0371)	(0.0365)	(0.0468)	(0.0364)
dummy	-0.0104	0.0477	0.0183	-0.0140	-0.0934	-0.0179	0.0036	0.0257	0.0231	-0.0463	-0.1422	-0.0156
	(0.0175)	(0.0234)	(0.0170)	(0.0217)	(0.0246)	(0.0158)	(0.0159)	(0.0167)	(0.0209)	(0.0280)	(0.0576)	(0.0067)

3.4.5 Comparison of Fit and Residual Diagnostics

The fit of the SD International CAPM is compared to the standard International CAPM. The result is reported in Table 3.9. Akaike Information Criterion (AIC)[57] is an estimate of the model's measure of fit (Akaike, 1974). According to the value of AIC, the average fit of the SD International CAPM and SD International three factor model is almost at the same level as that of the International CAPM with GARCH specifications -4.27, -4.26 and -4.28 respectively, while the average AIC values for the standard International CAPM and three factor models are -4.07 and -4.09 respectively.

The Bayesian (Schwarz) Information Criterion (SC) adds a penalty of 0.5k log T to the negative of the log likelihood, where k is the number of parameters in the model and T is the number of observations (Schwarz, 1978). The Hannan–Quinn information criterion (HQ) adds another penalty function to AIC (Hannan & Quinn, 1979). Likewise, the preferred model is the one with the lowest SC and HQ. The same results are observed for SC and HQ.

We also test properties of the SD International CAPM's residuals by applying Ljung–Box Q test statistics (Ljung & Box, 1978) for up to lag 4 (Table 3.10).[58] The results show only the presence of serial correlations for Brazil, Colombia, South Korea and the US market. Hence, it is interesting to test whether SD International CAPM improves the predictability of the model and whether that can better explain the variation in asset returns in emerging markets.

[57] AIC = ((-2) log-(maximum likelihood)/ number of observations) + 2((number of independently adjusted parameters within the model)/ number of observations).
[58] Following Chen (2003), Zhao (2010) and French (2017).

Table 3.9 Model fitting

This Table reports the values of log likelihood, Akaike Information Criterion (AIC), Bayesian (Schwarz) Information Criterion (SC) and Hannan-Quinn Criterion (HQ) as measures of model fitness. The fit of the SD International CAPM is compared to the unconditional CAPM and three-factor models. The BIC adds a penalty of 0.5k log T to the negative of the log-likelihood, where k is the number of parameters in the model and T is the number of observations. The preferred model is the one with the lowest AIC, SC or HQ. Overall, the fit of the SD International CAPM model is superior.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Unconditional International CAPM												
Log Likelihood	1551.75	1877.27	1682.38	1580.95	1674.39	1454.75	1282.81	1488.26	1664.20	1450.46	1614.38	1967.19
AIC	-3.82	-4.63	-4.15	-3.90	-4.13	-3.58	-3.16	-3.67	-4.10	-3.57	-3.98	-4.85
HQ	-3.81	-4.62	-4.14	-3.88	-4.12	-3.57	-3.15	-3.66	-4.09	-3.56	-3.97	-4.84
SC	-3.79	-4.60	-4.12	-3.87	-4.10	-3.56	-3.13	-3.64	-4.07	-3.54	-3.95	-4.82
International CAPM-GARCH-GED												
Log Likelihood	1659.24	1925.89	1772.91	1652.22	1724.46	1498.03	1461.08	1546.99	1702.33	1558.75	1746.39	2067.00
AIC	-4.09	-4.75	-4.37	-4.07	-4.25	-3.69	-3.60	-3.81	-4.19	-3.84	-4.30	-5.10
HQ	-4.07	-4.73	-4.35	-4.05	-4.23	-3.67	-3.58	-3.79	-4.18	-3.82	-4.29	-5.08
SC	-4.04	-4.70	-4.32	-4.02	-4.20	-3.64	-3.55	-3.76	-4.15	-3.79	-4.26	-5.05
Three-factor model												
Log Likelihood	1557.77	109.96	102.38	45.15	82.23	23.25	60.60	106.17	89.26	50.48	110.67	58.25
AIC	-3.83	-4.64	-4.16	-3.91	-4.12	-3.61	-3.16	-3.67	-4.15	-3.64	-4.02	-4.88
HQ	-3.82	-4.63	-4.14	-3.90	-4.11	-3.59	-3.15	-3.65	-4.13	-3.62	-4.00	-4.86
SC	-3.79	-4.60	-4.12	-3.87	-4.08	-3.57	-3.12	-3.63	-4.10	-3.60	-3.98	-4.84
SD International CAPM												
Log Likelihood	1647.80	1920.84	1776.45	1645.14	1732.86	1502.54	1426.57	1544.91	1714.30	1538.95	1732.72	2052.05
AIC	-4.05	-4.73	-4.37	-4.05	-4.26	-3.69	-3.51	-3.80	-4.22	-3.78	-4.26	-5.05
HQ	-4.03	-4.71	-4.35	-4.03	-4.24	-3.67	-3.48	-3.78	-4.20	-3.76	-4.24	-5.03
SC	-4.00	-4.67	-4.31	-3.99	-4.21	-3.64	-3.45	-3.74	-4.16	-3.73	-4.21	-5.00
SD Fama-French												
Log Likelihood	1655.03	1929.87	1781.91	1653.67	1735.05	1512.57	1435.65	1553.83	1737.76	1565.31	1746.75	2064.44
AIC	-4.06	-4.74	-4.38	-4.06	-4.26	-3.71	-3.52	-3.81	-4.27	-3.84	-4.29	-5.08

HQ	-4.03	-4.71	-4.34	-4.03	-4.23	-3.68	-3.49	-3.78	-4.24	-3.81	-4.26	-5.04
SC	-3.98	-4.66	-4.29	-3.98	-4.18	-3.63	-3.44	-3.73	-4.19	-3.76	-4.21	-4.99

Table 3.9 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Unconditional International CAPM												
Log Likelihood	1936.26	1602.54	1649.73	1598.74	1445.01	1147.23	1784.81	1762.81	1618.46	1252.31	996.93	2724.89
AIC	-4.77	-3.95	-4.07	-3.94	-3.56	-3.95	-4.40	-4.35	-3.99	-3.08	-3.43	-6.72
HQ	-4.76	-3.94	-4.05	-3.93	-3.55	-3.94	-4.39	-4.33	-3.98	-3.07	-3.42	-6.71
SC	-4.75	-3.92	-4.04	-3.91	-3.53	-3.91	-4.37	-4.32	-3.96	-3.05	-3.39	-6.70
International CAPM-GARCH-GED												
Log Likelihood	1983.17	1636.56	1724.18	1672.68	1548.61	1277.19	1808.99	1859.58	1678.97	1354.04	1096.13	2789.45
AIC	-4.89	-4.03	-4.25	-4.12	-3.81	-4.40	-4.46	-4.58	-4.14	-3.33	-3.77	-6.88
HQ	-4.87	-4.01	-4.23	-4.10	-3.80	-4.38	-4.44	-4.57	-4.12	-3.31	-3.75	-6.87
SC	-4.84	-3.98	-4.20	-4.07	-3.77	-4.34	-4.41	-4.54	-4.09	-3.29	-3.71	-6.84
Three-factor model												
Log Likelihood	235.69	92.61	44.79	119.17	116.01	22.83	165.70	90.76	62.53	60.54	23.90	982.37
AIC	-4.79	-4.01	-4.10	-3.94	-3.56	-3.96	-4.41	-4.37	-4.04	-3.09	-3.44	-6.72
HQ	-4.78	-3.99	-4.08	-3.92	-3.55	-3.94	-4.39	-4.35	-4.02	-3.08	-3.42	-6.71
SC	-4.75	-3.97	-4.06	-3.90	-3.52	-3.90	-4.37	-4.33	-4.00	-3.05	-3.38	-6.68
SD International CAPM												
Log Likelihood	1972.20	1667.69	1706.57	1671.52	1228.40	1253.46	1805.58	1833.92	1677.21	1337.19	1091.00	2783.56
AIC	-4.86	-4.10	-4.20	-4.11	-3.74	-4.31	-4.44	-4.51	-4.13	-3.29	-3.75	-6.87
HQ	-4.83	-4.08	-4.18	-4.09	-3.72	-4.28	-4.42	-4.49	-4.10	-3.26	-3.72	-6.84
SC	-4.80	-4.05	-4.14	-4.05	-3.67	-4.23	-4.39	-4.46	-4.07	-3.23	-3.67	-6.81
SD Fama-French												
Log Likelihood	1981.45	1687.61	1718.66	1671.18	1537.56	1255.41	1822.27	1865.99	1696.87	1345.01	1088.92	2793.40
AIC	-4.87	-4.14	-4.22	-4.10	-3.77	-4.30	-4.48	-4.58	-4.17	-3.29	-3.73	-6.88
HQ	-4.84	-4.11	-4.19	-4.07	-3.74	-4.26	-4.44	-4.55	-4.13	-3.26	-3.68	-6.85
SC	-4.79	-4.06	-4.14	-4.02	-3.69	-4.20	-4.39	-4.50	-4.08	-3.21	-3.62	-6.80

Table 3.10 Residual diagnostic test for SD International CAPM

This Table reports serial correlations of the SD International CAPM's residuals by applying Ljung–Box Q test statistics for up to lag 4.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Lag 2	0.013**	0.002	-0.008	0.062*	0.028	0.053*	0.020	-0.003	0.02	-0.015	-0.103***	0.029
Lag 3	0.065**	-0.026	0.06	0.058**	-0.003	-0.012	0.002	0.009	0.028	0.048	0.002**	-0.03
Lag 4	0.001*	0.018	-0.012	0.06**	-0.024	-0.014	-0.016	0.022	-0.05	0.077*	0.003**	0.017

Table 3.10 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Lag 2	0.002	0.053*	-0.003	0.002	0.029***	0.026	0.03	-0.045	0.022	-0.008	0.025	-0.062*
Lag 3	0.041	0.057*	0.01	-0.043	0.006	0.002	0.029	-0.001	0.014	0.008	-0.006	0.045*
Lag 4	-0.03	-0.03	0.015	-0.07	-0.017	0.1*	-0.059	-0.003	0.015	-0.024	0.005	0.042

Does SD International CAPM provide a superior conditional characteristic of the return's dynamic compared to alternative models such as GARCH? Testing the null hypothesis of no state dependency in the returns dynamic is essential, since the transition probabilities, p_{11} and p_{22} are unidentified (Hamilton, 1990). Table 3.11 presents the p-values of a Wald test of three restrictions, $h_0: \alpha_1 = \alpha_2$, $h_0: \beta_1 = \beta_2$ and $h_0: \sigma_1 = \sigma_2$. As expected, we do not reject the first restriction at a 5 per cent level of confidence, with the exceptions of Greece and India. However, the p-values for the second hypothesis suggest almost half of the emerging equity markets exhibit state dependency in their return's dynamic at a 5 per cent level of confidence, including those in the Americas (Brazil, Chile, Colombia, Mexico and Peru) as well as China, the Czech Republic, Egypt, Greece, India, Qatar and the UAE. The third restriction is also rejected for all equity markets at a 5 per cent level of confidence, suggesting that all the emerging markets are subject to two market volatility conditions.

3.4.6 Does SD International CAPM Explain the Asset Returns Better?

We carry out a visual comparison of the different models by plotting the fitted expected returns, computed using the estimated parameter values in each model specification, against the realized average excess returns. If the fitted expected returns and the realized average returns are the same, then all points should lie on the 45-degree line through the origin. This method has been used in previous similar studies (e.g., Jagannathan and Wang (1996); Abdymomunov and Morley (2011)).

Figure 3.4 depicts the predictability of the unconditional International CAPM and International CAPM with GARCH specification against the SD International CAPM for the 23 emerging markets and the US market. If the SD International CAPM showed an effective qualitative prediction for the variation of equity returns, then we should see points spread along the 45-degree line. This would imply that excess returns estimated by the International CAPM were equal to average realized excess returns. At first glance, the unconditional International CAPM gives very poor estimates of portfolio returns, despite the variation achieved for betas. The poor estimates of the International CAPM are consistent with previous studies (e.g., Fama and French (1992); Jagannathan and Wang (1996); Abdymomunov and Morley (2011); Vendrame et al. (2018)). The unconditional International CAPM estimates a flat prediction for excess returns, while the average realized excess returns vary significantly across different markets.

Table 3.11 P-values for hypothesis tests of SD International CAPM

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
$h_0: \alpha_1 = \alpha_2$	0.7429	0.5830	0.7029	0.6797	0.8459	0.0073	0.0001	0.2768	0.0796	0.3998	0.1908	0.9107
$h_0: \beta_1 = \beta_2$	0.0000	0.0472	0.0000	0.0095	0.0006	0.0900	0.0002	0.1527	0.0000	0.7116	0.8025	0.9373
$h_0: \sigma_1 = \sigma_2$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3.11 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
$h_0: \alpha_1 = \alpha_2$	0.9734	0.7618	0.2128	0.7392	0.8911	0.3573	0.7376	0.8920	0.6684	0.8569	0.1044	0.8384
$h_0: \beta_1 = \beta_2$	0.0414	0.0000	0.9975	0.8608	0.3053	0.0000	0.5938	0.3170	0.2022	0.9360	0.0279	0.2546
$h_0: \sigma_1 = \sigma_2$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000

The correlation coefficient between the excess returns estimated by the unconditional International CAPM and the average realized excess returns for the different markets has a value of -0.19, supporting the poor estimation of the unconditional International CAPM.[59] Despite the International CAPM-GARCH giving a contrary level of model fitness to the SD International CAPM (Table 3.9), the models yield flat results regarding the predictability of expected returns (though the correlation change to -0.10).

In comparison, the fitted excess returns estimated by the SD International CAPM improve across the two states. There is a clear improvement where we can see a more linear relationship between the SD International CAPM prediction, and the average realized excess returns. The correlation also changes to 0.53. This result suggests that the SD International CAPM can offer an improvement in the qualitative estimation of excess returns over the unconditional International CAPM, at least for high volatility states.

In comparison to the unconditional International CAPM, the excess returns estimation of the single three-factor model gives more variation to the expected returns across the markets (Figure 3.5). However, the SD International CAPM is still superior regarding the estimation of excess returns. The correlation coefficient increases to 0.51, which is closer to what we find in the unconditional International CAPM and International CAPM-GARCH. However, unlike the SD International CAPM which gives superior predictability to excess returns, the predictability of the state-dependent three-factor model remains at an almost equal level (0.46).

[59] This negative correlation is mainly due to average realized excess returns being negative for Greece and the UAE. However, removing negative returns, we still get a low correlation coefficient estimate.

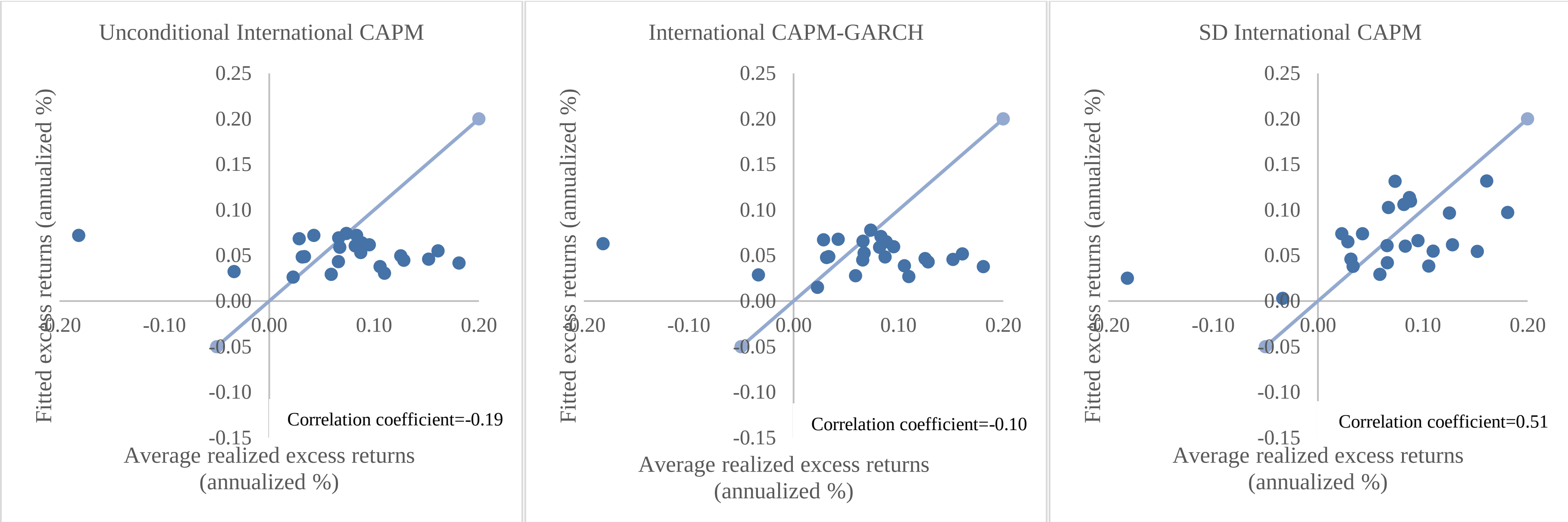


Figure 3.4 International CAPM fitted excess returns versus average realized excess returns for emerging market indices

The left scatter plot shows points of the average realized excess returns versus the fitted excess returns from equation (3.4), the unconditional International CAPM. The middle plot shows points of the average realized excess returns versus the fitted excess returns estimated with GARCH specification, and the right plot shows points of the average realized excess returns versus the fitted excess returns estimated SD International CAPM equation (3.16), conditional on smoothed probabilities of the high market volatility state being lower (higher) than 0.5. The fitted excess returns are computed as a product of estimated betas in the previous period state and realized market excess returns for observation, with smoothed probabilities of high market volatility being lower (higher) than 0.5. The straight lines on the graphs are 45-degree lines from the origins. The returns are computed as annualized.

Although most of the emerging markets selected for this study have experienced financial turmoil, some experienced particularly severe crises, and two countries had been considered to have segmented markets. For instance, Greece suffered a sovereign debt crisis after the GFC and this is shown by the high beta during the high volatility state. We also observed a higher market risk during the low volatility state for Brazil, which might be due to the economic crisis that intensified with the political crisis between 2014 and 2016. Russia is also considered a highly volatile market in both states. This can be explained by the fact that the country has experienced several crises over the past two decades, including the Russian financial crisis in 1998, the great recession in 2008–09, and more recently the currency crisis that hit the country in mid-2014. The two segmented markets are Qatar and the UAE. Excluding these markets can improve the performance of the models.

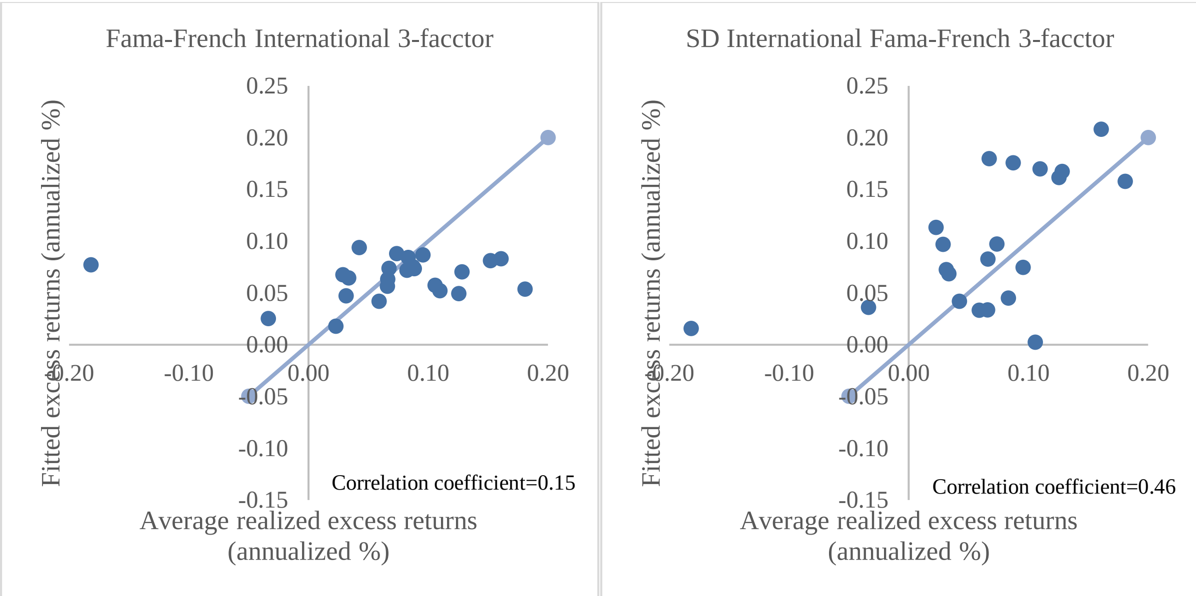


Figure 3.5 Factor model fitted excess returns versus average realized excess returns for emerging market indices

The left scatter plot shows points of the average realized excess returns versus the fitted excess returns from equation (3.17), the Fama and French three-factor model. The right scatter plot shows points of the average realized excess returns versus the fitted excess returns from equation (3.20), the state-dependent factor model, conditional on smoothed probabilities of the high market volatility state being lower (higher) than 0.5. The fitted excess returns are computed as a product of estimated betas in the previous period state and realized market excess returns for observation, with smoothed probabilities of high market volatility being lower (higher) than 0.5. The straight lines on the graphs are 45-degree lines from the origins. The returns are computed as annualized.

3.4.7 Robustness Tests

It is well known that the popular OLS model is very sensitive to outliers (because the outliers violate the assumption of normality) and volatility feedback (see footnote 13 for volatility feedback effect). In this Chapter, dummy variables and volatility feedback effect have been incorporated to account for extreme negative returns as well as volatility persistence. This is a common approach in asset pricing studies (Abdymomunov & Morley, 2011; Apergis & Rehman, 2018; Kim, Morley, & Nelson, 2004) with a view to determining coefficient sensitivity. I find the coefficients are consistent (Table 3.5 provides a comparison between models with and without dummy and volatility feedback effect). Dummy variables and volatility feedback have also been incorporated in SD International CAPM.

In this thesis, one of the main objectives was to test the CAPM with switching components (accounting for different market conditions) in emerging markets to see if the model is still valid. I robust checked the model by fitting the Fama-French three-factor model and demonstrate that this model provides inferior results, in terms of parameter significance and AIC. This strengthens my conclusion that the chosen model is relatively more efficient than commonly used benchmarks. Chapter 4 can be considered as an extension of Chapter 3 in the sense, I carry on by looking at US interest rate as one underlying factor that signal changes in market condition (as opposed to adding additional risk factors to the regression model).

Also, to assess model adequacy and check for serial correlation, the residual diagnostic testing has been done (Ljung-Box Q-Test in both Chapter 3, Table 3.10 and Chapter 4, Table 4.6). I used these tests to evaluate the relative fit of the SD models applied in addition to checking the AIC, HQ and SC. For instance, in terms of model fitness, the SD International CAPM outperforms its competitors. Also, most of the serial correlation observed in returns data (Table 3.1, Panel C) disappeared after SD models were fitted, further supporting my selection of SD models.

Following the common testing procedure done in the regime-switching model context (see, Henry, 2009), the null hypothesis of no state dependency in the returns dynamic were estimated and compared with the SD International CAPM to see if the latter provides superior conditional characteristics demonstrated through significant estimates (Table 3.11 Chapter 3 and Table 4.3 and 4.4 Panel B in Chapter 4).

3.5 Conclusion

Motivated by the theoretical background and empirical literature, in this chapter we test the explanatory power of state-dependent asset pricing models in emerging equity markets. This chapter contributes to the empirical research on the conditional International CAPM, first by accounting for time variation in betas relating to distinct volatility changes in the equity premium, and second by studying the explanatory power of the model during different market phases. we test whether time-varying global factors are state-dependent and help to explain the asset returns behaviour in emerging markets, by investigating time-varying global size and value factors along with the market risk premium to determine transition probabilities. Findings further support the argument that the lack of significance of global factors may be due to different market conditions.

First, we find that the volatility level in these markets changes significantly depending on the state of the economy, but a high level of volatility does not necessarily correspond to a high volatility state. Some markets also exhibit less volatility than expected despite fewer investment restrictions. This implies that markets with a lesser level of integration are priced locally. Hence, investors can optimize their returns by investing in these markets when world capital markets are in crisis. Second, the predictability of the SD International CAPM is stronger during business cycle recessions but weaker during expansions. This is consistent with previous studies that use state-dependent vector autoregression with predictors such as dividend yields and interest rates to capture the time-varying volatility of asset returns predictability in a state-dependent context (Henkel, Martin, & Nardari, 2011).

Third, we further augment the state-dependent model by adding global size and value risk factors to test whether a time-varying factor-model helps to explain asset pricing returns. Although the predictability of the global risk factors in Fama and French is significant in single state models, their explanatory power is small when the conditional three-factor model with the state-dependent condition is used.

Interest in emerging equity markets is increasing because of fast capital growth and the easing of regulation on foreign investment. Given the significant growth and effect of the emerging markets on the global economy, this chapter is useful for researchers as well as financial practitioners and managers, as it provides a model that can better explain asset pricing behaviour in emerging markets.

Chapter 4 The Dynamic Linkage between Emerging Equity Market Volatility and Macroeconomic Influences

4.1 Introduction

In Chapter 3, my aim was to test whether the expected returns in emerging markets can be explained by an SD International CAPM, where the market risk premium is used to identify market phases. That approach employed a Fixed Transition Probability (FTP). In this chapter, an SD International CAPM will be used to explain the expected returns in emerging markets, where we use changes in the interest rate level, in addition to changes in the market risk premium, to identify market phases. This approach employs time-varying transition probability (TVTP) to accommodate changes in interest rate levels. In this case, we allow the short-term interest rate to affect the transition probabilities. This model allows the short-term interest rate to show different behaviour during each market phase.

There is a long-held view in finance that a reduction in the level of short-term interest rates is associated with an increase in equity prices (Fama & Schwert, 1977). Most previous studies use the interest rate in conditional mean equations, thereby allowing only linear predictability (Reilly, Wright, & Johnson, 2007; Sweeney & Warga, 1986). However, studies such as (Chen, 2007) and Henry (2009) use interest rate risk both in mean equations and as a state predictor in a Markov-switching framework. In this chapter we allow the interest rate to influence only transition probabilities, so that the coefficients of expected returns can be estimated with more precision. This chapter aims to address the following question: does modelling market phases, as determined by changes in the level of interest rates in addition to volatility in the equity risk premium, better explain expected returns in emerging markets? This chapter is about augmenting the SD International CAPM with TVTP using volatility in the short-term and medium-term US interest rates (US monetary policy changes).

Over the last three decades, a number of empirical studies have investigated the impact of changes in target interest rates on equity markets.[60] For example, Campbell and Ammer (1993)

[60] Change in monetary policy implemented through changes in target interest rates may affect stock prices through three different sources. First, any change in the target rate will change the debt funding costs of a leveraged company and result in difference in the profitability of the company and possibly its dividend payments. Second, any change in the target rate may result in a change in the opportunity cost of equity investment, which affects stock prices. Third, changes in the target rate may affect business cycle conditions in the short to medium-term, this may affect the value of the stock by impacting the value of expected future cash flows (Henry, 2009).

find that asset prices are driven by news about future excess returns, news about future inflation and news about the short-term interest rate, combining the asset pricing framework with a vector autoregression method. Bernanke and Kuttner (2005) adopt a similar technique and find that unexpected changes to target rates account for the most significant part of the response of equity prices. Using a regression approach, Basistha and Kurov (2008) find that equity prices respond more strongly to monetary policy changes during a recession and in tight credit market conditions. Bredin, Hyde, Nitzsche, and O'reilly (2007) find support for the hypothesis that monetary policy changes cause a persistent negative response among future excess returns. These studies establish that interest rate fluctuations are associated with equity price movements and may also cause changes in the volatility level of equity returns.

Like prices in the equity markets, interest rates also exhibit stochastic behaviour. Changes in economic conditions and monetary policy may influence the level of expected inflation, which causes interest rates to vary over time. The Markov-switching models are an attractive class of models for determining the frequent and endogenous stochastic behaviour of interest rates (Ang & Bekaert, 2002b; Gray, 1996). Hamilton (1989) proposes a Markov-switching model where the probability of switching from one state to another is fixed, assuming a fixed expected duration for each state. Gray (1996) makes an extension to the Markov-switching models by allowing the short-term interest rate to exhibit both mean reversion and conditional heteroskedasticity, with time-varying transition probabilities dependent on the level of the short rate.

While equity return predictability has been a topic of debate in empirical financial studies, it remains unresolved due to lack of research on structural breaks in equity return dynamics. A recent strand of research characterizes equity returns as subject to state-dependent processes, where the states are dependent on macroeconomic variables. The influence of macroeconomic variables as state predictors has been investigated using the relationship between interest rates and equity return volatility (Chen, 2007; Henry, 2009).[61] The findings in Chen (2007) suggest that monetary policy changes have more influence on equity returns when prices are falling, and that there is a higher probability of switching to a bear market during periods of contractionary monetary policy. Henry (2009) on the other hand finds that there is a state-dependent relationship between short-term interest rates and stock return volatility in the UK market. Chang (2009) studies the effect of interest rates, dividend yields and default premia on the

[61] See also (Aloui & Jammazi, 2009) for the effects of crude oil volatility shocks on stock markets behaviour, Walid et al. (2011) for FX rate changes and stock market returns and Chen (2009) for yield curve spreads and inflation rates.

predictability of equity returns in the US market, finding that the effects of these variables are time-varying, but are closely linked to variability in equity returns, and that predictability in the high volatility state is stronger than in the normal state.

Although a number of studies have used interest rates to explain equity price movements in domestic markets (Conover et al., 1999; Ehrmann & Fratzscher, 2009; Georgiadis, 2016; Kim, 2009; Nave & Ruiz, 2015; Yang & Hamori, 2014), there have been few studies that examine the linkage between changes in US monetary policy and international equity markets. While a variety of approaches have been employed in these studies, they all found a relationship between US monetary policy changes and international equity markets. For example, Yang and Hamori (2014) employ a Markov-switching framework and report evidence that the spillover effect of US monetary policy differs depending on the market phases (i.e., bull markets and bear markets), and that monetary policy has more influence on international equity markets during a bull market than in a bear market. Distinguishing this from prior studies, we look at US monetary policy changes as a global market condition in order to study the risk-return relationship worldwide by employing an International CAPM to explain the expected returns in emerging equity markets, using monetary policy changes in addition to time-varying risk premium to identify the market phases in emerging markets.

The method we adopt in this chapter is a combination of two approaches: the International form of Solnik's (1974) CAPM and Filardo's (1994)state-dependent model with time-varying transition probabilities. Filardo (1994) develops a Markov-switching model which assumes that the probability of switching may be governed by some leading economic indicators. He allows time-varying transition probabilities that are functions of underlying economic fundamentals to identify the business cycle.

This chapter reflects previous research which characterized the expected returns based on market phases, where the switching process in returns is governed by the volatility in market risk premium (Abdymomunov & Morley, 2011; Huang, 2003; Ramchand & Susmel, 1998; Vendrame et al., 2018). However, in this chapter we extend the analysis by incorporating an additional variable, the interest rate, to identify the world market phases.

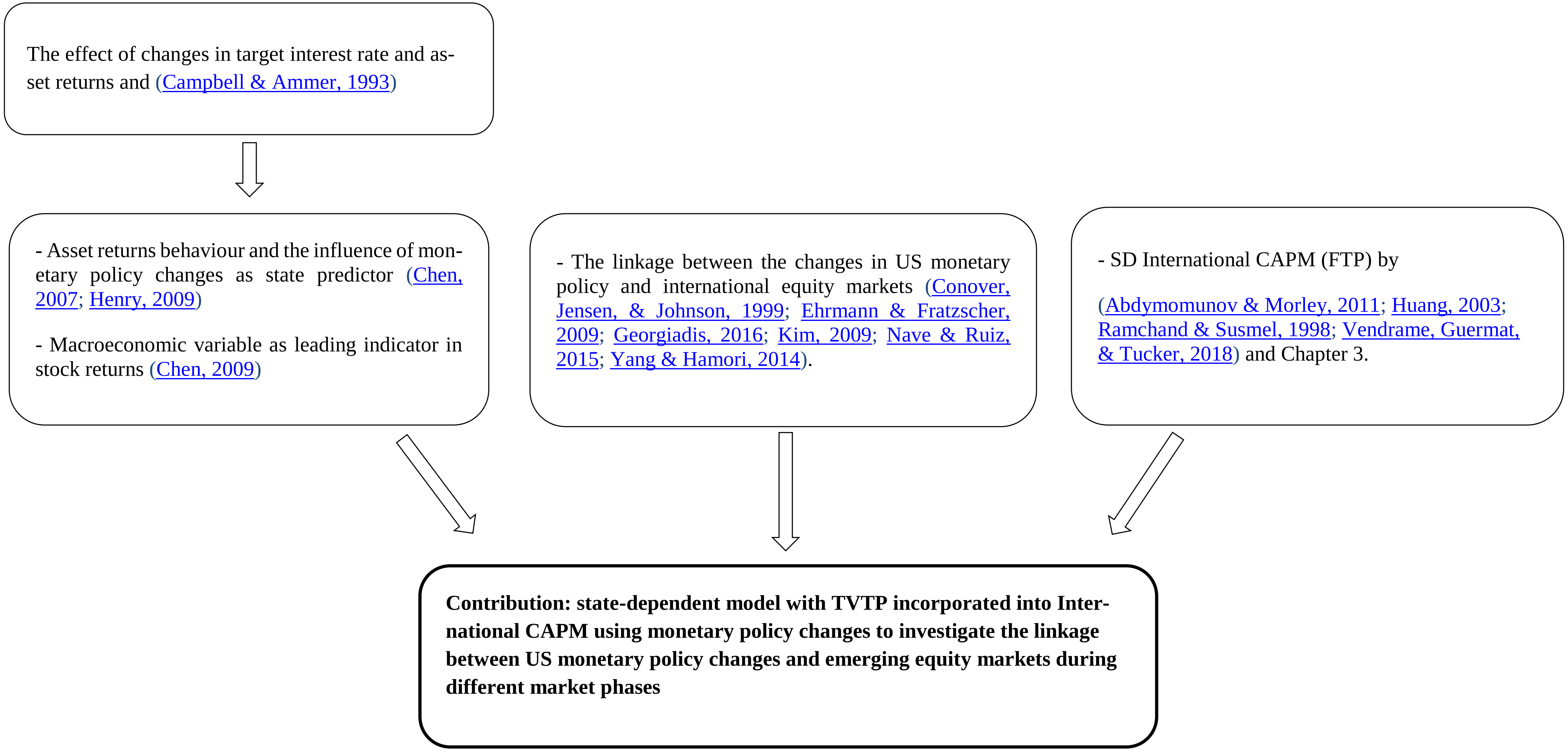
State-dependent models with time-varying transition probabilities have not previously been incorporated into the International CAPM. Unlike prior asset pricing models that employ the interest rate to capture the variation in expected returns (see, e.g., (Campbell, 1996; English, Van Den Heuvel, & Zakrajšek, 2018; Sweeney & Warga, 1986)), the model proposed in this chapter uses the interest rate to identify volatility in asset prices but does not directly affect the expected return estimates. Unlike prior research, this chapter investigates how changes in US monetary policy affect equity returns volatility, with a focus on emerging economies.

This chapter is organized as follows: Section 2 reviews the literature and the hypotheses we aim to test, Section 3 describes the methodology and Section 4 discusses data selection and empirical findings. The conclusion will be presented in Section 5.

4.2 Literature Review

The first part of this section gives an overview on regime-switching in asset pricing models. The second part gives an overview on the effect of monetary policy changes on international equity markets, leading to the hypothesis that we aim to test in this chapter. Figure 4.1 depicts key papers that have led to the development of the SD International CAPM with TVTP used in this chapter.

Figure 4.1 Literature review and chapter contributions



4.2.1 Regime-switching in Asset Pricing Models

The predictability of equity returns has been a topic of debate in empirical financial studies; however, researchers have not come to a solid conclusion. One factor contributing to this has been uncertainty regarding the identification of structural breaks, i.e. asymmetric volatility, in the equity return dynamic.[62] One strand of research characterizes equity returns as a state-dependent process where the states are dependent on macroeconomic variables.

The influence of macroeconomic variables as state predictors has been investigated, with variables including interest rates and equity return volatility (Henry, 2009), the effects of crude oil volatility shocks on stock markets behaviour (Aloui & Jammazi, 2009), and FX rate changes and stock markets (Walid et al., 2011). Henry (2009) finds that there is a state-dependent relationship between the short-term interest rate and stock return volatility in the UK equity market. Chang (2009) studies the effect of the interest rate, dividend yield and default premium on the predictability of equity returns in the US market, finding that the effects of these variables are time-variant, but closely linked to variability in equity returns, and that predictability in the high volatility state is stronger than in the normal state.

The second strand of research characterizes asset returns using the CAPM where the switching process in returns is governed by volatility in the market risk premium (Abdymomunov & Morley, 2011; Huang, 2003; Ramchand & Susmel, 1998; Vendrame et al., 2018). Like those studies, this chapter incorporates a Markov-switching framework into the International CAPM, but we use changes in interest rates to characterize the volatility in the market risk premium and to identify world market phases.

The Markov-switching models are helpful in determining casual but frequent and endogenous regime-switching behaviour in economic and financial time series. Hamilton (1989) proposes a Markov-switching model where the probability of switching from one state to another is fixed, assuming a fixed expected duration for each state. Filardo (1994) develops a Markov-switching model assuming that some leading economic indicators govern the probability of

[62] For example, the asymmetric volatility response to a drop in asset prices could reflect the presence of time-varying volatility in the market risk premium (Campbell & Hentschel, 1992). If volatility is priced into assets, an expected increase in volatility increases the required return on stock, resulting in stock price decline. While the leverage hypothesis states that drops in asset prices lead to changes in conditional volatility, the time-varying risk premium theory states that drops in asset prices are caused by changes in conditional volatility (Bekaert & Wu, 2000), though the main determinant of causality remains an open question.

switching. He allows time-varying transition probabilities that are functions of underlying economic fundamentals to identify business cycles. Gray (1996), on the other hand, extends the Markov-switching models by allowing the short-term interest rate to exhibit both mean reversion and conditional heteroskedasticity, with time-varying transition probabilities dependent on the level of the short-term rate. Ang and Bekaert (2002b) find that Markov-switching models incorporating international short-term rate spread information provide better forecasts than single state models, and that movement in interest rates is a component in the determination of the business cycle.

4.2.2 Monetary Policy Changes and International Equity Returns

There is considerable literature documenting the integration of financial markets as one of the financial changes that causes equity prices to show higher co-movement (see, e.g., (Bekaert & Harvey, 2014; Gupta & Guidi, 2012; Hanauer & Linhart, 2015; Junior & Franca, 2012)). Therefore, it is reasonable to expect that US monetary policy may impact not only domestic equity prices but also international equity prices.

Craine and Martin (2008) were among the first to study the effects of international monetary policy surprise and to measure the responses of equity markets to monetary and non-monetary shocks in the US and Australia. They found that a US monetary surprise is a world surprise and that this helps to explain variations in equity returns. Ehrmann and Fratzscher (2009) study the transmission of US monetary policy surprises to international equity markets and the macroeconomic determinants of this transmission. They find that equity markets with a greater degree of integration,[63] as well as economies with a more volatile exchange rate regime, react more to US monetary surprises. Georgiadis (2016), on the other hand, argues that the transmissions of US monetary policy shocks depend on country characteristics (such as market openness and development, exchange rate regime, industry structure, and participation in global value chains), and varies across developed and emerging economies. From another point of view, Rey (2015) argues that global financial conditions (leverage of global banks, capital flows and credit growth in the international financial system) are determined by a global economic cycle, which appears to be driven by US monetary policy.

Kim (2009) investigates the spillover effects of US and European target rate news on equity market returns and volatilities in the Asia-Pacific. They find that an unexpected increase in

[63] Factors such as well-developed equity markets, openness to foreign ownership as well as capital outflows from domestic market to international markets are used to measure the degree of integration.

target rates is associated with negative returns in these markets, and that the level of equity market volatility is higher when there is target rate news. Further, Yang and Hamori (2014) provide evidence of the spillover effect of the US target rate on Association of Southeast Asian Nations (ASEAN) equity markets using a Markov-switching framework. They find that this effect differs depending on the market phase; US monetary policy has more influence on ASEAN equity markets during bull markets than in bear markets. More importantly, they suggest that a decrease in the level of the US short-term rate has a positive effect on equity returns in the next period.

Based on the above discussion, the following hypothesis will be tested in this chapter:

Hypothesis: When the US short-term interest rate is high, equity returns tend to be low with high volatility, and when the US short-term interest rate is low, equity returns tend to be high with low volatility.

This chapter furthers understanding of the linkage between international equity market returns and monetary policy changes in the US. More precisely, it is related to and contributes to asset pricing models and their macroeconomic determinants, first by employing the state-dependent time-varying transition probability in the International CAPM, and second by studying the macroeconomic determinants of international equity markets.

4.3 Method

The TVTP of the Markov-switching model allow for two distinctive market phases with state-dependent expected returns and volatility based on recurrent changes in predetermined variables: in this case, market risk premium as an endogenous variable and interest rate as an exogenous variable. The model assumes that market phases cannot be specified with certainty, so investors can neither observe the phase of the market nor derive the state directly. However, the states are supposed to be path dependent and follow the Markov chain process of order one with TVTP coefficient (Filardo, 1994).

In this chapter the TVTP of Filardo (1994) is incorporated into the International CAPM using the quasi-Newton optimization technique. Unlike existing Markov-switching models, the model developed in this chapter is quite flexible, enabling it to capture not only state dependence in the market risk premium as an endogenous variable but also the asymmetric response to a shock in an economic-indicator variable as an exogenous variable.

In this section, we begin by describing first the SD International CAPM with FTP, then the extension of the model into TVTP.

4.3.1 State-dependent International CAPM (FTP)

Following Kim and Nelson (1999), Solnik (1974), and recalling Chapter 3, we jointly model the market and the excess return portfolios as follows:

$$r_{m,t} = \mu_{m,0} + \mu_{m,1}\Pr[S_{m,t} = 1|S_{m,t-1}] + \varepsilon_{m,t} \qquad \varepsilon_{m,t} \sim N(0, \sigma^2_{m,S_{m,t}}) \tag{4.1}$$

$$r_{it} = \ \alpha_{i,s_t} + \beta_{i,S_t} r_{mt} + \varepsilon_{i,s_t} \varepsilon_{i,s_t} \sim N\left(\, 0, \sigma^2_{i,s_t}\right) \tag{4.2}$$

$$\beta_{i,s_t} = \beta_1(1 - S_t) + \beta_2 s_t$$

$$\sigma^2_{i,s_t} = \sigma_1^2(1 - S_t) + \sigma_2^2 S_t$$

$$S_t = 1 \; or \; 2 \text{ and } t = 1, 2\,, \ldots T$$

Where under state 1, parameters are given by β_1 and σ_1^2, and under state 2, parameters are given by β_2 and σ_2^2. If S_t is known a priori, the structural breaks are known; thus, equation (4.1) can be adjusted for a dummy variable where the dummy variable, S_t, is 0 in state 1 and 1 in state 2.[64] However, the challenge arises when S_t is not observed for $t = 1, 2\,, \ldots T$ and the market phases are not known a priori.[65] In this scenario, the following two steps are necessary to determine the log-likelihood function (Hamilton, 1989; Kim & Nelson, 1999):

Step1. First, suppose the joint conditional and marginal densities of r_{it} and the latent variable, s_t:

$$f(r_{it}, s_t|\phi_{t-1}) = f(r_{it}|s_t, \phi_{t-1})\, f(s_t|\phi_{t-1}) \tag{4.3}$$

Where ϕ_{t-1} refers to information available up to time $t - 1$.

Step2. To get the marginal density of r_{it}, we need to bring the s_t variable out of the equation (4.2) by summing all possible values of s_t (in this case, $s_t = j, j = 1 \; and \; 2$).

[64] See for example Nyberg (2012), who combines a regime-switching model with a probit model using binary values as business cycle indicators in terms of expansion and recession.

[65] Equation (4.2) is the regression form of International CAPM with structural breaks in parameters.

$$f(r_{it}|\phi_{t-1}) = \sum_{s_t=1}^{2} f(r_{it}, s_t|\phi_{t-1}) = \sum_{s_t=1}^{2} f(r_{it}|s_t, \phi_{t-1}) f(s_t|\phi_{t-1}) \tag{4.4}$$

$$= \frac{1}{\sqrt{2\pi\sigma_1^2}} exp\left\{\frac{-(r_{it} - \alpha_1 - \beta_1 r_{mt})^2}{2\sigma_1^2}\right\} \times Pr[s_t = 1|\phi_{t-1}]$$

$$+ \frac{1}{\sqrt{2\pi\sigma_2^2}} exp\{\frac{-(r_{it} - \alpha_2 - \beta_1 r_{mt})^2}{2\sigma_2^2}\} \times Pr[s_t = 2|\phi_{t-1}]$$

The log likelihood is then given by getting log from equation (4.4):

$$ln\ L = \sum_{t=1}^{T} ln\{\sum_{s_t=1}^{2} f(r_{it}|s_t, \phi_{t-1}) Pr[s_t|\phi_{t-1}]\} \tag{4.5}$$

(Appendix B).

The marginal density in equation (4.4) can be defined as a weighted average of the conditional densities given $s_t = 1$ and $s_t = 2$ respectively. To obtain the marginal density of r_{it} in equation (4.4), and therefore the log likelihood function, the weighting factors $Pr[s_t = 1|\phi_{t-1}]$ and $Pr[s_t = 2|\phi_{t-1}]$ should be calculated. But without prior information about the stochastic behaviour of the state variable this would be impossible, so the following section outlines the assumptions about the transition of the state variable and explains an appropriate approach to calculate the weighting factors given in equation (4.4), based on the first-order Markov chain process.

The transition of the latent variable s_t may be dependent on the past only through the most recent value s_{t-1} (Hamilton, 1994). In the case of a two-state, first-order Markov chain, the process for s_t is given by the following transition probabilities:

$$Pr\{s_t = j|s_{t-1} = i\} = p_{ij} = \begin{bmatrix} p_{i1} \\ p_{i2} \end{bmatrix} = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix} \tag{4.6}$$

This process is called a two-state Markov chain with transition probabilities $\{p_{ij}\}$ for $i, j = 1, 2$. The transition probability p_{ij} gives the probability that state i will be followed by state j (Appendix A).

$$p_{11} = \frac{exp(\theta_1)}{1+exp(\theta_1)} \text{ and } p_{22} = \frac{exp(\eta_1)}{1+exp(\eta_1)} \tag{4.7}$$

Recalling that the model allows for two states, assuming s_t= 1 denotes a low variance state and s_t= 2 denotes a high variance state, then σ^2_{i,s_t} is defined as conditional variance[66] of residuals where $\sigma^2_{i,2} > \sigma^2_{i,2}$. In fact, $s_t$depends on the past realization of r_{it} and the current state only through s_{t-1}.

Step1. Given $Pr[s_{t-1} = i|\phi_{t-1}]$, for $i = 1, 2$, at the beginning of time t or the t-th iteration, the weighting terms $Pr[s_t = j|\phi_{t-1}]$ for $j = 1, 2$, are calculated as

$$\begin{aligned} Pr[s_t = j|\phi_{t-1}] &= \sum_{i=1}^{2} Pr[s_t = j, s_{t-1} = i|\phi_{t-1}] \\ &= \sum_{i=1}^{2} Pr[s_t = j|\ s_{t-1} = i]\, Pr[s_{t-1} = i|\phi_{t-1}] \end{aligned} \tag{4.8}$$

Where $Pr[s_t = j|\ s_{t-1} = i]$, $i = 1, 2$ and, $j = 1, 2$ are transition probabilities.

Step2. Once r_{it} is observed at the end of time t or the t-th iteration, the probability term can be revised as follows:

$$\begin{aligned} Pr[s_t = j|\phi_t] = Pr[s_t = j|\phi_{t-1}, r_{it}] &= \frac{f(s_t = j, r_{it}|\phi_{t-1})}{f(r_{it}|\phi_{t-1})} \\ &= \frac{f(r_{it}|s_t = j, \phi_{t-1}) Pr(s_t = j|\phi_{t-1})}{\sum_{j=1}^{2} f(r_{it}|s_t = j, \phi_{t-1})\, Pr(s_t = j|\phi_{t-1})} \end{aligned} \tag{4.9}$$

Where $\phi_t = \{\phi_{t-1}|r_{it}\}$.

The above two steps may be iterated to get $Pr[s_t = j|\phi_t]$, $t = 1, 2, \ldots T$. To begin the above process at time $t = 1$, we require $Pr[s_1|\phi_1]$.

The solution to finding the unconditional probability of each state is to $|P - \lambda I_N| = 0$ (Where I_N is 2×2 identity matrix in the case of two states). Following the process given by Hamilton (1994), the unconditional probability that the process is in state 1 and state 2 at any given time is:

$$P\{s_t = 1\} = \frac{1-p_{22}}{2-p_{11}-p_{22}}\ and\ P\{s_t = 2\} = \frac{1-p_{11}}{2-p_{11}-p_{22}} \tag{4.10}$$

[66] We could have either a conditional mean or a conditional variance model.

The marginal density in equation (4.4), as well as the log likelihood function, is now a function of unknown parameters $(\alpha_1, \alpha_2, \beta_1, \beta_2, \sigma_1^2, \sigma_2^2)$ which can be estimated numerically (Hamilton, 1994) (Appendix B).

4.3.2 State-dependent International CAPM (TVTP)

Following Filardo (1994) and extending the assumption of fixed transition probabilities by altering the transition probability matrix in equation (4.6) to be dependent on the macroeconomic variable yields the TVTP. The two-point stochastic process on s_t can be stated using the following time-varying transition matrix:

$$p_{ij}(z_{m,t}) = \begin{bmatrix} p_{11}(z_{m,t}) & 1 - p_{22}(z_{m,t}) \\ 1 - p_{11}(z_{m,t}) & p_{22}(z_{m,t}) \end{bmatrix} \tag{4.11}$$

Where $p_{ij}(z_{m,t}) = Pr\{s_t = j | s_{t-1} = i, z_{m,t}\}$ for $i, j = 1, 2$ and where the history of the economic-indicator variable is $z_{m,t} = \{i_{m,t}, i_{m,t-1}, \dots\}$. The interest rate differentials $\Delta z_{m,t} = i_{m,t} - i_{m,t-1}$ measure the slope of the yield curve for the US. In fact, $\Delta z_{m,t} = i_{m,t} - i_{m,t-1}$ (for m = three-month interest rate and five-year bond) captures changes in the yield curve for different maturities.

The time-varying transition matrix governs any movement between the two states. Volatility in $z_{m,t}$ will directly affect the probabilities of switching across the states and varying over time. Now it is possible to explore how news in the money market leads to changes not only in the volatility and expected returns of r_{it} but also in the probabilities of changes in market phases.

The model in equation (4.1) characterizes the market risk premium where volatility in the short-term rate and five-year bond determine time-varying transition probabilities between the two market phases. However, testing the null hypothesis of no state-dependency in the market risk premium is a necessary condition, since the transition probabilities are unobserved. To test the existence of two distinctive market phases, the state-dependent mean and state-dependent standard deviation should be statistically different. Further, testing whether μ_1 and μ_2 are positive and negative respectively is a required condition to show that the model is representing bull and bear markets.

Filardo (1994) suggests the logistic functional form for tests of time-varying probabilities and the statistical significance of the coefficients of the economic variable $z_{m,t}$. In this specification, p_{11} and p_{22} are positive and are bounded between (0, 1) to a well-characterized log-likelihood function.

$$p_{11} = \frac{exp(\theta_1+\theta_2 z_{m,t-1})}{1+exp(\theta_1+\theta_2 z_{m,t-1})} \text{ and } p_{22} = \frac{exp(\eta_1+\eta_2 z_{m,t-1})}{1+exp(\eta_1+\eta_2 z_{m,t-1})} \tag{4.12}$$

This function and its restriction are necessary conditions for performing the likelihood ratio test. Under the null hypothesis of no time variation in the transition probabilities, in the FTP model, $\theta_2 = \eta_2 = 0$. L_1 is defined as the value of the log-likelihood under the null hypothesis of no time variation in the transition probabilities, and L_2 as the same measure under the alternative. The FTP model is not accepted if $LR = 2(L_2 - L_1)$ exceeds $\chi^2_{(2)}$ for two parameters.

Note that the signs of θ_2 and η_2 govern the time-varying probabilities. For example, if $\widehat{\theta_2}$ increases and $\widehat{\eta_2}$ decreases when $z_{m,t}$ increases (good news), both the transition probability from state 1 to state2 rises and the transition probability from state 2 to state 1 rises (Filardo, 1994). Regardless of the phase of the market at time t, the probability of being in state 1 at time $t + 1$ increases. In another word, for $\widehat{\theta_2} > 0$, good news to $z_{m,t}$ indicates that equity returns are more likely to stay in state 1. Alternatively, $\widehat{\theta_2} < 0$ indicates that equity returns are less likely to stay in state 1 following good news to $z_{m,t}$. In this specification, for transition probabilities, the good news of $z_{m,t}$ is measured by the opposite signs of θ_2 and η_2.

4.3.3 Log-likelihood Function

In TVTP, the parameters in equation (4.2) and transition probability parameters in equation (4.11) can jointly be estimated (Filardo, 1994). The conditional joint density function compiles the information from the dataset and directs the transition probabilities to the estimation techniques and tests. Following Filardo (1994), we can write the conditional density, f^*, as:

$$f^*\left(r_{it}\middle|\phi_{t-1}, z_{m,t}; \theta\right) \tag{4.13}$$
$$= \sum_{s_t=1}^{2} f\left(r_{it}, s_t\middle|\phi_{t-1}, z_{m,t}; \theta\right)$$
$$= \sum_{s_t=1}^{2} \hat{f}(r_{it}|s_t; \theta) \times P\left\{s_t = j\middle|s_{t-1} = i, z_{m,t}\right\}$$
$$\times P\left\{s_{t-1} = i\middle|\phi_{t-1}, z_{m,t-1}\right\}$$

Where $(\theta \equiv \alpha_1, \alpha_2 , \beta_1, \beta_2, \sigma_1^2 , \sigma_2^2)'$, determining the conditional density. If the process is in state 1, the observed variable r_{it} is drawn from a $N(\mu_1, \sigma_1^2)$ distribution. Alternatively, if the process is in state 2 then r_{it} is drawn from a $N(\mu_2, \sigma_2^2)$ distribution. Therefore, the density of r_{it} is conditional on the random variable $s_t = j$ in equation (4.13).

The log-likelihood function is then given by taking the log of equation (4.13):

$$L(\theta) \ = \sum_{t=1}^{T} ln\left[f^*\left(r_{it}\middle|\phi_{t-1}, z_{m,t}; \theta\right)\right] \tag{4.14}$$

Equation (4.13) specifies the information contained in the market risk premium and the economic variable $z_{m,t}$. These two sources of information affect the parameters estimation both directly and indirectly through the inference of the past states. The information in $r_{it}$and ϕ_{t-1} directly affects the probability through the normal density, $\hat{f}$; ϕ_{t-1} indirectly influences the probability through the information it brings about the past state $P\left\{s_{t-1} = i\middle|\phi_{t-1}, z_{m,t-1}\right\}$. The economic variable directly influences the transition probabilities $P\left\{s_t = j\middle|s_{t-1} = i, z_{m,t}\right\}$ and indirectly influences the states distribution, $P\left\{s_{t-1} = i\middle|\phi_{t-1}, z_{m,t-1}\right\}$. In this study, the TVTP model, $\hat{f}$, is independent of $z_{m,t}$ and is not a function of the economic variable $z_{m,t}$ (Filardo (1994)). This chapter adds TVTP to the International CAPM to derive the potential effects of monetary policy surprises on international equity markets and to understand the dynamics of market phases. The advantage of the model is that it is possible to separate out the marginal effect of monetary policy as an indicator of the inference about the global equity market phases.

One attribute of the Markov-switching framework is that the model assumes the state of the economy/market is unobserved. In a Markov-switching model with TVTP, information available in both $\phi_{t-1}$and $z_{m,t}$ is combined to derive market phases. To evaluate the impact of time variation in transition probabilities on inferences about market phases, there must be a clear link between the transition probabilities and the expectations of the market phases equation (4.11). Following Filardo (1994), the expectations of the market phases at time t can be estimated by integrating the past states effects in joint density-distribution as follows:

$$P\left(s_t = i|r_{it}, z_{m,t}; \theta\right) = \sum_{s_t=1}^{2}\left(s_t = i|r_{it}, z_{m,t}; \theta\right) = \frac{\sum_{s_t=1}^{2} f\left(r_{it}, s_t\middle|\phi_{t-1}, z_{m,t}; \theta\right)}{f^*\left(r_{it}\middle|\phi_{t-1}, z_{m,t}; \theta\right)} \tag{4.15}$$

The transition probabilities affect the density-distribution, f, and therefore directly influence the expectation of the market phases through the numerator in the third part of equation (4.15). Accordingly, the TVTP model of Filardo (1994) is an alternative to the FTP of (Hamilton, 1989; Hamilton, 1990) when an economic variable contains information about the evolution of the market phases.

4.4 Data and Empirical Results

The equity markets used for this chapter are the same as those used in Chapter 3, comprising 23 emerging markets according to the MSCI Emerging Market indices collected from financial data collected from the TFD data bank. We use weekly returns, calculated as the logarithmic of the total return for each value-weighted index. To maintain consistency of results, we collect weekly returns in US dollars for all of the indices. The length of the sample is not uniform and depends on the availability of data. The data runs from January 2001 to June 2016 for all of the equity markets except Qatar and the UAE, which begin in June 2005. Proxy for the world financial market index is the MSCI world total return index reported by MSCI. All returns are calculated in excess of the one-month US T-bill rate. US macroeconomic factors are the three-month short-term rate and the five-year bond yield (see Appendix E Table E2 for interest rate variables description).

4.4.1 Summary Statistics

Table 4.1 reports summary statistics of the weekly first difference US three-month interest rate and five-year bond. The first difference in interest rate variables was integrated to the order of 1, I (1), with the result of Dickey-Fuller test statistics less than the 1 per cent critical value (-2.56), indicating that the first difference in interest rates is stationary. The short-term rate also indicates a high level of kurtosis, showing volatility clustering (major shocks of either sign occur more frequently) and that the interest rate series are more likely to show non-normality. The results for Q-statistics are significant at a 1 per cent level for up to four lags, implying significant serial correlation in the residuals, and this has spikes at lag one. These results indicate that there is strong evidence of autocorrelation in both the three-month interest rate and the five-year bond, suggesting that a model with an AR component would be more appropriate. However, it is important to note that in this chapter these two variables only influence the transition probabilities and did not incorporate into mean equations. Most previous studies use the interest rate in a conditional mean equation, thereby allowing only linear predictability (Reilly et al., 2007; Sweeney & Warga, 1986). On the other hand, studies such as (Chen, 2007) and Henry (2009) use interest rate risk both in the mean equation and as a state predictor in a Markov-switching framework.

Figure 4.2 shows the stochastic behaviour of the US short-term rate and five-year bond in Panels A1 and A2, and volatility clustering in Panels B1 and B2, respectively. It is evident that a high variance state corresponds to economic recession, as indicated in the shaded bars which show NBER recession times. Panels C1 and C2 of Figure 4.2 display the smoothed probabilities of Model 2 and Model 3 respectively. The smoothed (ex-post) probability is the likelihood, given all the information present in the data sample, that the state in the next period, for the market risk premium, will be the high-mean low-variance state: the normal state. Visually there is no obvious difference between the two models; however, the long-run smoothed probability of being in a high-mean low-variance state is 0.91 and 0.93 for Models 2 and 3 respectively, whereas it is 0.95 for model 1 with FTP.

4.4.2 Market Risk Premium Estimation (TVTP)

Throughout this chapter the t statistic measures as the difference between the regression coefficients $\hat{\alpha}$ and $\hat{\beta}$, and the hypothesised coefficients α and β, divided by the standard error of the regression coefficients ($t = \frac{\hat{\beta}-\beta}{SE_{\hat{\beta}}}$). Using a 1 per cent level of significance, the critical value of the t test would be 2.57; using a 5 per cent level of significance, the critical value would be 1.96; and using a 10 per cent level of significance, the critical value would be 1.64.

Table 4.1 Summary statistics for the weekly first differences in 3-month T-bill and 5-year bond reported in annualized percentage terms

The sample period is from January 2001 to June 2016, a total of 809 observations. The interest rate variables were integrated to the order of 1, I (1) with the result of Dickey-Fuller test statistics less than the 1 per cent critical value (-2.56). The data are plotted in Fig. 4.1 Panel B1 and B2.

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF test	AR (1)	AR (2)	AR (3)	AR (4)
Short-term rate	-0.0063	0.0889	-3.3229	38.0540	42909.0200	-8.659455***	0.155***	0.01***	0.049***	0.081***
5-year bond	-0.0049	0.1078	0.0768	4.1616	46.2799	-23.1265***	0.202***	0.049***	0.018***	-0.008***

Figure 4.2 plots the values of p_{11} and p_{22} given different values of $\Delta z_{m,t}$, the three-month interest rate and the five-year bond differential respectively.

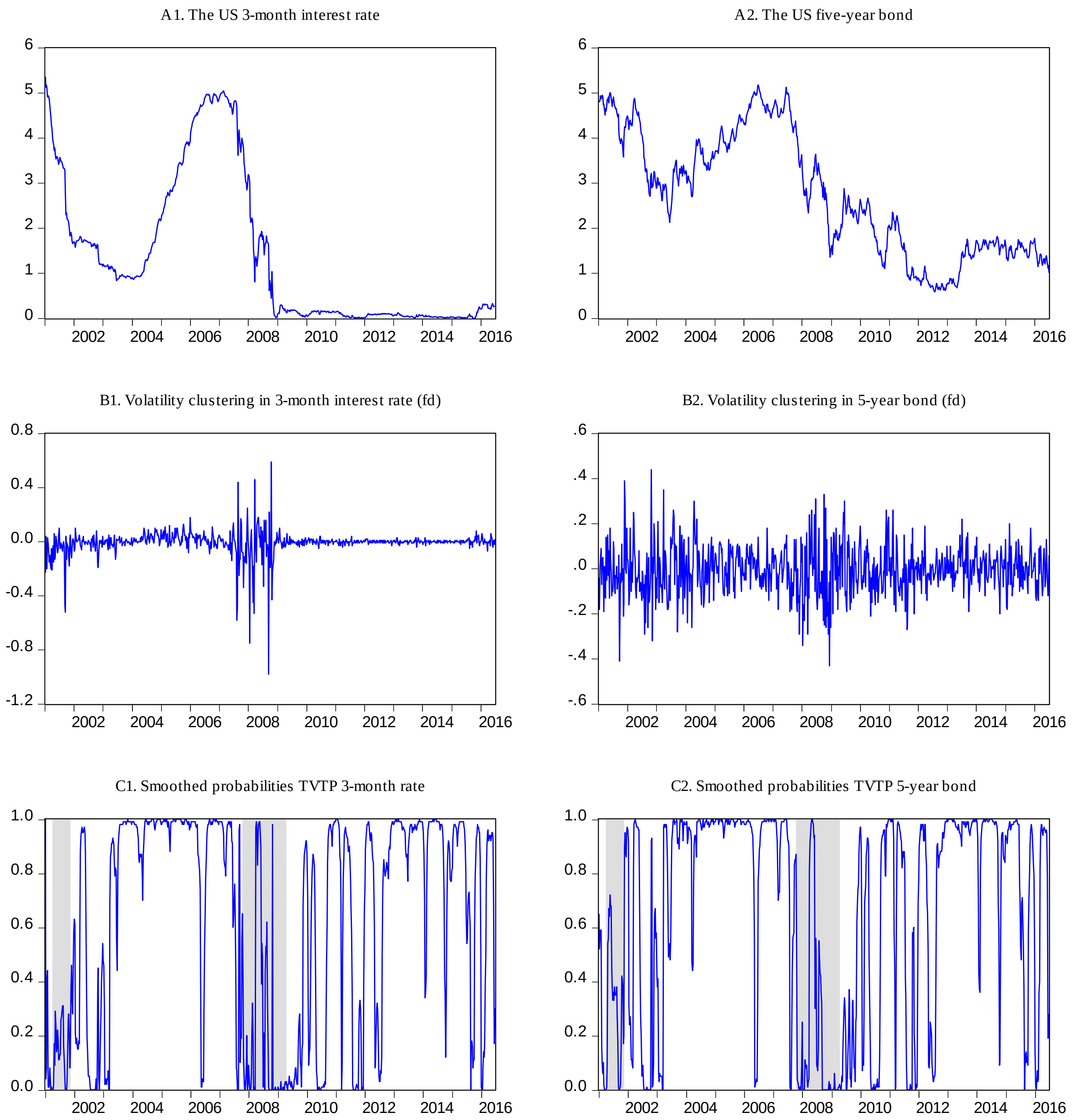


Figure 4.2 Volatility in 3-month US T-bill and 5-year bond rates

Panels A1 and A2 depict the stochastic behavior of the short-term rate interest rate and five-year bond in the US. Panels B1 and B2 show the volatility in the short-term rate and five-year bond at first difference, and Panels C1 and C2 display the visual of smoothed probabilities based on Model 2 and Model 3 in Table 4.2 respectively. The shaded bars show NBER recessions.

First, we test the model of the market risk premium with FTP versus the model with TVTP where volatility in the short-term rate and the five-year bond determines the time-varying transition probabilities between the two market phases. The maximum likelihood estimation results associated with various specifications are given in Table 4.2. We assume that state 1 corresponds to a high-mean low variance market phase (bull market) and state 2 corresponds to a low-mean high-variance market phase (bear market) (Chen, 2007; Henry, 2009). Based on model 1, the estimations of θ_1 and η_1 are significant and indicate that p_{11} is 0.9580 and p_{22} is 0.9241 respectively: equation (4.7). The persistence of state 1 and state 2 is 23.98 and 13.19 weeks respectively: equation (4.10). The model estimates average returns of 0.16 per cent and -0.20 per cent per annum for state 1 and state 2 respectively.

Is there evidence of regime-switching in the market risk premium? We test the null hypothesis of no switching in market risk premium against an alternative. Table 4.2 shows the results of a Wald test for $h_0: \mu_1 = \mu_2$ and $h_0: \sigma_1 = \sigma_2$. Both restrictions are rejected for all three models at 1 per cent level of confidence indicating the results are consistent with the evidence of two market phases in market risk premium (bull market and bear market). In addition, in the case of model 2 and model 3 with TVTP, the statistical significance of the null hypothesis of FTP, $H_0: \theta_2 = \eta_2 = 0$, provides evidence of a state-dependent response by the market risk premium to US money market surprises. These findings indicate the existence of time variation in transition probabilities which is influenced by interest rate movements. The p-value for the Wald test is significant at a 1 per cent level of confidence for the null hypothesis of FTP ($h_0: \theta_2 = \eta_2 = 0$).

How can market phases be determined by changes in interest rate level? The signs of θ_2 and η_2 govern the time-varying probabilities (Filardo, 1994; Henry, 2009). For example, for $\theta_2 > 0$, good news (positive shock) to $z_{m,t}$ indicates that equity returns are more likely to stay in state 1. Alternatively, $\theta_2 < 0$ indicates that equity returns are less likely to stay in state 1 following good news to $z_{m,t}$. In this specification, for transition probabilities, the effect of $z_{m,t}$ is measured by the opposite signs of θ_2 and η_2. But in Model 2 and Model 3, positive signs for both θ_2 and η_2 may reflect the fact that the short-term rate decreases as a bear market begins, and increases as a bull market begins.

Table 4.2 State-dependent parameters estimates for volatility and market risk premium with TVTP

This Table shows parameters estimation for market risk premium with FTP, Model 1, and with TVTP, Model 2 and 3 in the 3-month US T-bill and 5-year bond respectively. The world markets return expressed in equation (4.1). Transition matrix parameters are from equation (4.12). The results of the Wald test for the existence of two market phases and time-varying probabilities are also presented. Standard errors are in parenthesis. Log L stands for log likelihood.

	μ_1	μ_2	σ_1	σ_2	θ_1	θ_2	η_1	η_2	$H_0: \mu_1 = \mu_2$	$H_0: \sigma_1 = \sigma_2$	$H_0: \theta_2 = \eta_2 = 0$	log L
Model 1	0.0034	-0.0046	0.0144	0.0359	3.129		-2.510					1961.20
	(0.0008)	(0.0022)	(0.0002)	(0.0006)	(0.000)		(0.000)		0.001	0.000		
Model 2	0.0035	-0.0042	0.0139	0.0354	3.073	21.866	-2.339	9.295				
	(0.0007)	(0.0021)	(0.0002)	(0.0005)	(0.000)	(0.015)	(0.000)	(0.016)	0.001	0.000	0.003	1967.70
Model 3	0.0032	-0.0043	0.0142	0.0364	3.417	13.154	-2.499	8.988				
	(0.0007)	(0.0023)	(0.0002)	(0.0006)	(0.476)	(4.526)	(0.401)	(2.801)	0.002	0.000	0.000	1970.45

The left panel of Figure 4.3 suggests that as $\Delta z_{m,t}$ increases, the probability of staying in state 1, p_{11}, is almost one, and that for some large negative observations of $\Delta z_{m,t}$, p_{11} falls. The right panel of Figure 4.3 suggests that when $\Delta z_{m,t} = 0$, the implied probability of remaining in state 2 is about 0.91. It is apparent that when $\Delta z_{m,t} < 0$ the probability of staying in state 2 increases. But relatively small increases in three-month interest rate are associated with a high probability of remaining in state 2. Given the statistically significant values of θ_2 and η_2, the time variations in p_{11} and p_{22} may be economically reasonable. This evidence implies that the market risk premium is more likely to remain in the low-mean high variance state (state 2) when the interest rate falls, as was the case during the GFC.

The left panel of Figure 4.4 suggests that when $\Delta z_{m,t} = 0$ the probability of remaining in state 1, p_{11}, is almost one. When the five-year bond starts to increase $\Delta z_{m,t} > 0$, there is no visible effect on p_{11} as the probability remains almost one. On the other hand, the right panel of Figure4.4 suggests that when $\Delta z_{m,t} = 0$, the probability of remaining in state 2 is about 0.92. The right panel of Figure4.4 also suggests that for $\Delta z_{m,t} < 0$ the probability of staying in state 2 increases. But as the five-year bond starts to increase $\Delta z_{m,t} > 0$, the probability of staying in state 2 decreases. Given the statistically significant values of θ_2 and η_2, the results suggest an important economic intuition of the usefulness of interest rate movement and equity returns.

4.4.3 State-dependent International CAPM (TVTP)

Table 4.3 shows the estimates for the SD International CAPM with time-varying transition probability defined in equation (4.2) for 23 emerging markets and the US market. First, significant intercepts are observed for Colombia, the Czech Republic, Egypt, India, Indonesia, and the Philippines in state 1, Greece in state 2 and Peru in both states. Second, consistent with the result in the previous chapter, we did not find any trend, shown by changes in betas, towards high or low-risk states; that is, the results do not imply any clear pattern for this assumption. More specifically, we do not observe higher value for $\hat{\beta}$ estimates for markets in the high volatility phase, e.g., Brazil, Korea, Malaysia and South Africa. These results are inconsistent with the theoretical assumption about volatility behaviour, which states that financial markets are more correlated to each other in bad times (Junior & Franca, 2012; Longin & Solnik, 2001).

Figure 4.3 Time-varying probabilities in market risk premium and changes in 3-month US T-bill rate

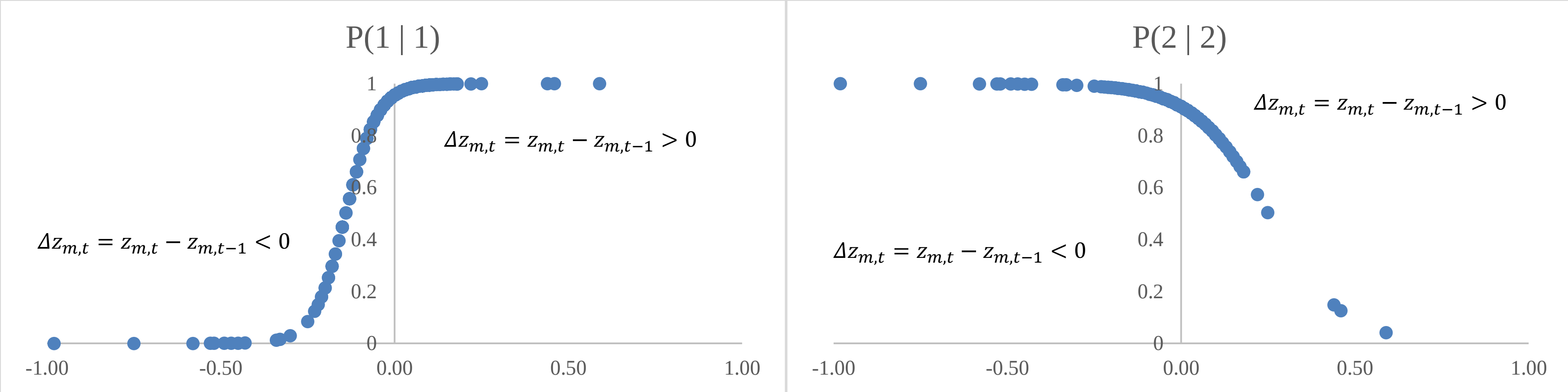
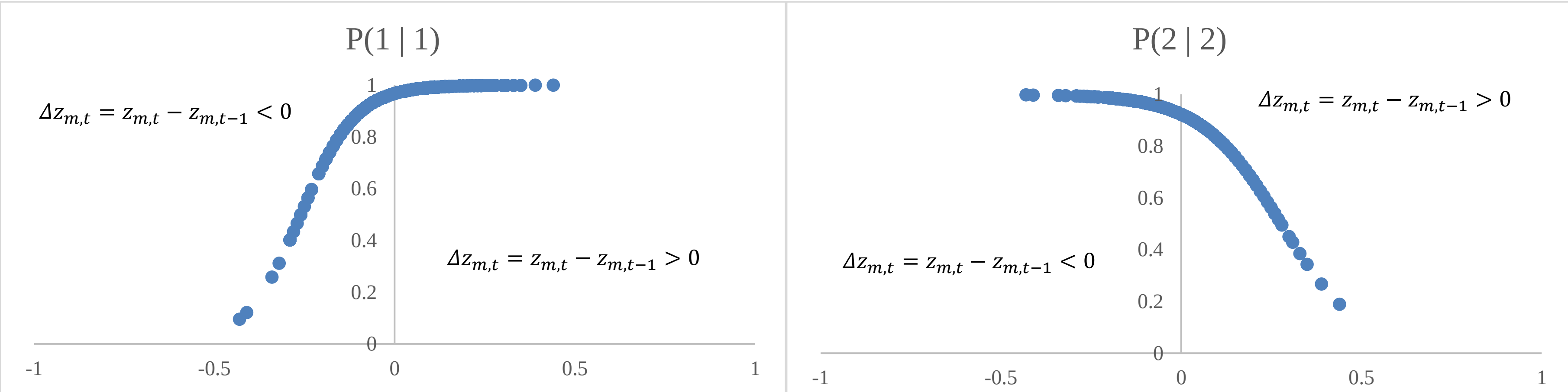


Figure 4.4 Time-varying probabilities in market risk premium and changes in 5-year bond rate



But consistent with the results in the previous chapter, we observe a low value for $\hat{\beta}$s for Egypt, India, Malaysia, Peru, the Philippines and Qatar, implying less volatility relative to world equity markets. These findings may confirm the fact that the assets in these markets are priced locally, and the risks come from local factors such as domestic economic factors or idiosyncratic volatility. We find the state-dependent beta coefficients are significant at the 1 per cent level. This evidence implies that the estimated beta from the unconditional International CAPM underestimates the risk premium under the high volatility state while overestimating the risk premium under the low-volatility state. In comparison, the SD International CAPM can allow the market risk, beta, to be drawn from two different states to characterize the instability of beta that was found in previous studies.

Table 4.4 shows the results of the SD International CAPM with a time-varying transition probability defined in equation (4.2) for my sample set, using the five-year bond as a time-varying probability. The results of $\hat{\alpha}$ and $\hat{\beta}$ are quite like what we achieve with the short-term rate as a time-varying probability (Table 4.3).

Table 4.3 SD International CAPM (TVTP) in 3-month interest rate

The results of regression analysis where the dependent variables are weekly returns on MSCI indices for 23 emerging markets and the US market. The independent variable is the weekly return on world equity market in excess of the one-month T-bill rate. The TVTP does not directly affect the parameters estimation. Panel A reports the estimates for alphas, betas and standard deviations for the state-dependent International CAPM with time-varying transition probability described by equation (4.2). Panel B reports the estimates for time-varying probability parameters. Panel C reports the p-values for hypothesis tests. Standard errors are in parentheses.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Panel A - State-dependent alphas, betas and standard deviations												
α_1	0.0007	0.0006	0.0005	0.0033	0.0022	0.0070	0.0020	0.0016	0.0027	0.0040	0.0002	0.0006
	(0.0011)	(0.0009)	(0.0009)	(0.0014)	(0.0010)	(0.0016)	(0.0014)	(0.0013)	(0.0011)	(0.0012)	(0.0009)	(0.0007)
α_2	-0.0003	0.0016	0.0020	0.0036	0.0056	-0.0068	-0.0120	-0.0044	-0.0016	-0.0035	0.0054	0.0008
	(0.0067)	(0.0031)	(0.0026)	(0.0033)	(0.0065)	(0.0045)	(0.0039)	(0.0087)	(0.0028)	(0.0066)	(0.0049)	(0.0022)
β_1	1.4765	0.8637	0.8528	0.5055	0.7748	0.4690	1.0464	1.1857	0.6281	0.8242	1.1449	0.5962
	(0.0572)	(0.0449)	(0.0458)	(0.0644)	(0.0509)	(0.0783)	(0.0587)	(0.0851)	(0.0661)	(0.0634)	(0.0501)	(0.0373)
β_2	1.2620	0.8464	1.2475	1.4097	1.4364	0.7523	1.6599	1.8036	1.3341	0.9536	1.1733	0.4877
	(0.1902)	(0.0882)	(0.0915)	(0.1972)	(0.1592)	(0.1364)	(0.1896)	(0.2814)	(0.0928)	(0.1862)	(0.1349)	(0.0698)
σ_1	0.0264	0.0179	0.0199	0.0244	0.0256	0.0243	0.0272	0.0311	0.0238	0.0271	0.0234	0.0151
	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0002)	(0.0005)	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
σ_2	0.0687	0.0379	0.0433	0.0012	0.0549	0.0572	0.0690	0.0753	0.0407	0.0727	0.0594	0.0320
	(0.0022)	(0.0011)	(0.0006)	(0.0014)	(0.0020)	(0.0013)	(0.0012)	(0.0039)	(0.0008)	(0.0026)	(0.0014)	(0.0006)
Panel B - Time-varying probability parameters												
θ_1	4.5657	3.2600	4.4912	3.5550	4.1151	1.2461	4.2937	3.3276	4.3294	2.6158	5.5362	4.8141
	(0.6510)	(0.5143)	(0.5730)	(0.5563)	(0.5332)	(0.3826)	(0.6506)	(0.5059)	(0.5458)	(0.3546)	(1.0660)	(0.8255)
θ_2	8.7771	18.6602	-11.3118	-37.5282	-8.4998	1.1579	4.0617	-6.1575	13.8880	18.8734	15.6050	-19.2279
	(2.8557)	(10.3081)	(12.4176)	(13.6722)	(4.7466)	(2.6912)	(3.1023)	(4.3362)	(4.9665)	(8.4659)	(6.8659)	(8.7747)
η_1	-3.3180	-1.4882	-3.7092	-1.9709	-1.7563	-0.4999	-4.5866	-0.9293	-3.0889	-0.6325	-3.2208	-3.2886
	(0.8305)	(0.4467)	(0.4987)	(0.5403)	(0.4843)	(0.5456)	(1.0186)	(0.6948)	(0.4345)	(0.6055)	(0.6464)	(0.5830)
η_2	-17.5580	4.1697	2.3330	-2.5554	0.3469	-0.4126	-13.8855	0.9300	0.3762	0.2065	6.6538	5.9263

	(6.8664)	(5.1187)	(3.2643)	(2.6104)	(2.2003)	(2.0008)	(5.3138)	(2.6834)	(3.1206)	(1.8706)	(2.9099)	(3.7435)
Panel C - P-values for hypothesis tests												
$h_0: \alpha_1 = \alpha_2$	0.8932	0.7695	0.5874	0.9349	0.6090	0.0090	0.0009	0.5048	0.1709	0.2808	0.2988	0.9321
$h_0: \beta_1 = \beta_2$	0.2993	0.8732	0.0002	0.0000	0.0001	0.1077	0.0022	0.0560	0.0000	0.5364	0.8494	0.1977
$h_0: \sigma_1 = \sigma_2$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$h_0: \theta_2 = \eta_2 = 0$	0.0022	0.1190	0.5637	0.0127	0.2006	0.9104	0.0297	0.3536	0.0193	0.0669	0.0117	0.0334

Table 4.3 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Panel A - State-dependent alphas, betas and standard deviations												
α_1	0.0017	0.0030	0.0030	0.0001	0.0010	0.0016	-0.0001	-0.0002	0.0018	0.0008	0.0019	0.0002
	(0.0009)	(0.0017)	(0.0011)	(0.0011)	(0.0014)	(0.0010)	(0.0010)	(0.0008)	(0.0011)	(0.0016)	(0.0015)	(0.0003)
α_2	-0.0010	0.0064	-0.0020	-0.0015	0.0008	-0.0017	0.0032	0.0011	0.0028	-0.0009	-0.0122	-0.0001
	(0.0027)	(0.0023)	(0.0038)	(0.0079)	(0.0051)	(0.0035)	(0.0026)	(0.0027)	(0.0032)	(0.0049)	(0.0083)	(0.0010)
β_1	0.9321	0.3764	0.6496	1.2083	1.4253	0.2658	1.3118	0.8619	0.7709	1.2793	0.5476	0.8925
	(0.0399)	(0.0928)	(0.0548)	(0.0833)	(0.0734)	(0.0451)	(0.0547)	(0.0415)	(0.0541)	(0.0779)	(0.0661)	(0.0166)
β_2	1.9983	1.6597	0.7233	1.5140	1.5475	0.8787	1.0838	0.9130	0.9086	1.5248	1.0539	0.9468
	(0.0937)	(0.1217)	(0.1319)	(0.4384)	(0.1540)	(0.1227)	(0.0820)	(0.0857)	(0.1209)	(0.1697)	(0.2142)	(0.0278)
σ_1	0.0194	0.0274	0.0221	0.0267	0.0280	0.0167	0.0228	0.0192	0.0232	0.0371	0.0283	0.0066
	(0.0002)	(0.0006)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0005)	(0.0000)
σ_2	0.0222	0.0356	0.0498	0.0695	0.0680	0.0499	0.0359	0.0412	0.0488	0.0752	0.0796	0.0134
	(0.0006)	(0.0007)	(0.0014)	(0.0029)	(0.0018)	(0.0010)	(0.0006)	(0.0006)	(0.0009)	(0.0015)	(0.0029)	(0.0002)
Panel B - Time-varying probability parameters												
θ_1	2.2793	3.9602	2.8827	3.8582	3.7588	2.9566	5.9045	6.4974	3.6161	7.4902	3.8539	2.7442
	(0.7028)	(0.5628)	(0.5822)	(0.4566)	(0.4825)	(0.3546)	(1.1766)	(1.2535)	(0.4303)	(2.4261)	(0.5383)	(0.6401)
θ_2	3.2175	0.3296	20.8459	3.4589	2.2776	3.4642	25.5354	55.7246	-3.6737	73.8639	-4.7603	-4.6817
	(3.7998)	(26.3607)	(12.0451)	(3.3844)	(3.9112)	(3.0852)	(16.0241)	(17.0923)	(5.1867)	(33.4761)	(4.9548)	(3.6167)
η_1	-0.3566	-4.0028	-1.3619	-1.8207	-2.6488	-2.3712	-3.5981	-3.5580	-2.7414	-4.5956	-2.3614	-5.3486
	(1.1528)	(0.6288)	(0.4794)	(0.5196)	(0.5938)	(0.3679)	(0.7230)	(0.5380)	(0.4481)	(1.1577)	(0.4560)	(0.9443)
η_2	-24.5592	0.6122	-0.7712	-9.2491	2.0867	-0.8196	5.5088	-4.3032	-0.3144	33.1810	0.2360	-35.9949

	(21.7369)	(8.2954)	(2.1928)	(5.9073)	(3.2645)	(2.3557)	(4.4201)	(2.7272)	(3.4462)	(15.5358)	(3.0589)	(11.2424)
Panel C - P-values for hypothesis tests												
$h_0: \alpha_1 = \alpha_2$	0.3947	0.2906	0.2278	0.8413	0.9814	0.3731	0.2510	0.6414	0.7787	0.7390	0.1001	0.7869
$h_0: \beta_1 = \beta_2$	0.0000	0.0000	0.6407	0.5421	0.5088	0.0000	0.0315	0.6013	0.3386	0.2011	0.0254	0.1117
$h_0: \sigma_1 = \sigma_2$	0.2559	0.0432	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$h_0: \theta_2 = \eta_2 = 0$	0.3077	0.9952	0.2170	0.1312	0.7050	0.5238	0.0498	0.0028	0.7713	0.0065	0.6255	0.0019

Table 4.4 SD International CAPM (TVTP) in 5-year bond

The results of regression analysis where the dependent variables are weekly returns on MSCI indices for 23 emerging markets and the US market. The independent variable is the weekly return on world equity market in excess of the one-month T-bill rate. The TVTP does not directly affect the parameters estimation. Panel A reports the estimates for alphas, betas and standard deviations for the state-dependent International CAPM with time-varying transition probability described by equation (4.2). Panel B reports the estimates for time-varying probability parameters. Panel C reports the p-values for hypothesis tests. Standard errors are in parentheses.

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
Panel A - State-dependent alphas, betas and standard deviations												
α_1	0.0003	0.0007	0.0005	0.0038	0.0023	0.0061	0.0019	0.0016	0.0034	0.0041	0.0006	0.0006
	(0.0011)	(0.0008)	(0.0009)	(0.0012)	(0.0010)	(0.0015)	(0.0014)	(0.0013)	(0.0011)	(0.0013)	(0.0010)	(0.0007)
α_2	0.0010	0.0011	0.0020	0.0024	0.0033	-0.0052	-0.0128	-0.0058	-0.0050	-0.0050	0.0035	0.0011
	(0.0054)	(0.0033)	(0.0026)	(0.0046)	(0.0063)	(0.0038)	(0.0046)	(0.0091)	(0.0039)	(0.0074)	(0.0047)	(0.0021)
β_1	1.5236	0.8803	0.8557	0.5566	0.7838	0.4097	1.0322	1.2078	0.7196	0.8492	1.1555	0.5797
	(0.0566)	(0.0498)	(0.0462)	(0.0514)	(0.0579)	(0.0601)	(0.0687)	(0.0726)	(0.0773)	(0.0650)	(0.0552)	(0.0559)
β_2	1.2306	0.8264	1.2403	1.6296	1.3584	0.8539	1.7272	1.7404	1.2883	0.9028	1.1553	0.5112
	(0.1584)	(0.0893)	(0.0925)	(0.2009)	(0.1764)	(0.1350)	(0.2046)	(0.2659)	(0.1324)	(0.1959)	(0.1231)	(0.0778)
σ_1	0.0257	0.0188	0.0200	0.0258	0.0251	0.0245	0.0272	0.0308	0.0242	0.0279	0.0224	0.0141
	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0003)	(0.0003)	(0.0003)
σ_2	0.0637	0.0383	0.0436	0.0520	0.0551	0.0566	0.0704	0.0777	0.0451	0.0747	0.0578	0.0317
	(0.0018)	(0.0009)	(0.0007)	(0.0015)	(0.0019)	(0.0010)	(0.0017)	(0.0036)	(0.0012)	(0.0030)	(0.0015)	(0.0008)

Panel B - Time-varying probability parameters												
θ_1	4.7301	6.2413	4.7353	3.6717	3.8044	1.5297	4.0102	3.4860	5.5887	3.0225	5.0938	4.4612
	(0.7502)	(1.8240)	(0.9406)	(0.5571)	(0.4863)	(0.3677)	(0.5797)	(0.5709)	(1.0332)	(0.4921)	(0.8777)	(0.8817)
θ_2	10.9043	27.4027	9.1065	-13.9348	4.2350	10.5807	-6.2522	9.5705	20.6891	7.8270	15.2185	17.6192
	(4.2249)	(10.1090)	(9.7851)	(3.6442)	(7.5758)	(3.2411)	(3.6766)	(3.2909)	(6.7360)	(3.4368)	(5.0831)	(5.0816)
η_1	-3.0798	-2.1510	-4.2111	-1.7470	-1.6502	-1.0226	-4.1602	-0.5257	-2.6750	-0.9504	-2.7759	-2.5067
	(0.9246)	(0.4255)	(0.7603)	(0.6453)	(0.5194)	(0.5508)	(1.0637)	(0.6527)	(0.5326)	(0.6696)	(0.6818)	(0.4322)
η_2	8.1187	1.4494	8.5913	8.3760	4.1604	-25.1449	-11.8215	0.1840	-6.1341	0.8118	3.1866	0.1334
	(5.3346)	(4.4152)	(4.9259)	(5.6478)	(3.7411)	(8.9660)	(6.0606)	(3.4898)	(5.2034)	(3.4217)	(4.2934)	(6.7696)
Panel C - P-values for hypothesis tests												
$h_0: \alpha_1 = \alpha_2$	0.9035	0.9175	0.5906	0.7840	0.8874	0.0099	0.0024	0.4280	0.0455	0.2400	0.5550	0.8192
$h_0: \beta_1 = \beta_2$	0.0929	0.6350	0.0003	0.0000	0.0042	0.0046	0.0007	0.0723	0.0011	0.8084	0.9989	0.5556
$h_0: \sigma_1 = \sigma_2$	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$h_0: \theta_2 = \eta_2 = 0$	0.0229	0.0240	0.1867	0.0005	0.4162	0.0002	0.0595	0.0128	0.0080	0.0530	0.0074	0.0023

Table 4.4 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
Panel A - State-dependent alphas, betas and standard deviations												
α_1	0.0019	0.0029	0.0022	0.0000	0.0013	0.0015	-0.0002	0.0001	0.0018	0.0004	0.0020	0.0002
	(0.0009)	(0.0015)	(0.0011)	(0.0010)	(0.0013)	(0.0010)	(0.0009)	(0.0008)	(0.0011)	(0.0016)	(0.0014)	(0.0003)
α_2	-0.0014	0.0023	0.0002	-0.0007	0.0000	-0.0013	0.0042	0.0002	0.0028	-0.0006	-0.0120	-0.0001
	(0.0026)	(0.0017)	(0.0036)	(0.0063)	(0.0053)	(0.0032)	(0.0029)	(0.0028)	(0.0032)	(0.0059)	(0.0079)	(0.0019)
β_1	0.9298	0.3556	0.6297	1.2498	1.3969	0.2758	1.3006	0.8982	0.7668	1.3568	0.5428	0.8984
	(0.0412)	(0.0726)	(0.0563)	(0.0573)	(0.0814)	(0.0444)	(0.0483)	(0.0445)	(0.0541)	(0.0785)	(0.0654)	(0.0157)
β_2	1.9491	1.3893	0.7596	1.3205	1.5733	0.8483	1.0803	0.8762	0.9149	1.4231	1.0534	0.9489
	(0.1055)	(0.0674)	(0.1402)	(0.1774)	(0.1563)	(0.1168)	(0.0841)	(0.0814)	(0.1222)	(0.1876)	(0.2116)	(0.0343)
σ_1	0.0192	0.0235	0.0213	0.0258	0.0279	0.0160	0.0229	0.0192	0.0231	0.0382	0.0281	0.0069
	(0.0002)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0005)	(0.0000)
σ_2	0.0231	0.0360	0.0494	0.0649	0.0697	0.0484	0.0373	0.0416	0.0485	0.0811	0.0789	0.0151
	(0.0005)	(0.0004)	(0.0016)	(0.0022)	(0.0018)	(0.0010)	(0.0007)	(0.0006)	(0.0009)	(0.0019)	(0.0027)	(0.0003)

Panel B - Time-varying probability parameters												
θ_1	2.0060	4.2952	2.4793	4.2991	4.2784	3.1835	6.1296	7.2277	3.8229	5.3649	-3.8404	7.4286
	(0.3798)	(0.7034)	(0.6092)	(0.6555)	(0.5682)	(0.5023)	(1.2383)	(1.4013)	(0.5093)	(0.7301)	(0.5499)	(1.7711)
θ_2	-0.3500	4.1609	-9.0342	12.5593	12.6413	-12.9511	11.5675	24.8423	-8.0490	2.6949	-4.2398	29.8220
	(2.2750)	(9.1893)	(5.2263)	(4.3164)	(4.2278)	(5.2866)	(9.8182)	(7.3926)	(5.6704)	(11.4979)	(9.1873)	(9.0724)
η_1	-0.5642	-4.5486	-1.1843	-1.5737	-2.7362	-2.3730	-6.1324	-4.0286	-2.9230	-4.3190	2.4107	-2.2686
	(0.9637)	(0.6018)	(0.7390)	(0.4130)	(0.6627)	(0.3903)	(1.9336)	(0.7305)	(0.6476)	(0.6960)	(0.4724)	(0.5305)
η_2	-60.9023	-1.8557	0.7818	0.9583	8.4970	2.3697	13.8279	2.4703	-3.7657	1.2551	2.9709	-0.0035
	(38.8241)	(6.5256)	(3.1803)	(5.4695)	(4.8142)	(4.5272)	(7.2445)	(5.3656)	(5.0404)	(19.5137)	(3.6556)	(6.4877)
Panel C - P-values for hypothesis tests												
$h_0: \alpha_1 = \alpha_2$	0.2525	0.8150	0.6108	0.9216	0.8142	0.4196	0.1455	0.9599	0.7856	0.8743	0.0877	0.8657
$h_0: \beta_1 = \beta_2$	0.0000	0.0000	0.4422	0.7228	0.3610	0.0000	0.0266	0.8169	0.3106	0.7521	0.0228	0.2012
$h_0: \sigma_1 = \sigma_2$	0.0542	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$h_0: \theta_2 = \eta_2 = 0$	0.2865	0.8700	0.1832	0.0098	0.0019	0.0496	0.1388	0.0032	0.2786	0.9701	0.6945	0.0044

4.4.4 Does News in the US Money Market Have Spillover Effects in International Equity Markets?

The TVTP estimates show that three-month interest rate information brings positive and negative shocks (good news and bad news) to equity markets (Panel B of Table 4.3). For example, when both θ_1 and θ_2 ($\eta_1$and η_2) have statistically significant identical signs, it may reflect that the interest rate tends to increase during a bull market if signs are positive (bear market if negative). These results are given for Brazil and Taiwan in both states, Chile, India, India, Indonesia, Korea, Philippines, Taiwan, Turkey in state 1 (bull market), and Greece in state 2 (bear market) at a 10 per cent level of confidence. In addition, when both θ_2 and η_2 have statistically significant opposite signs, it may suggest that the transition probabilities, p_{11} and p_{22}, fluctuate as $\Delta z_{m,t}$ changes. For example, the results for Brazil (Taiwan) ($\theta_2 > 0$ and $\eta_2 < 0$) may suggest that the probability of remaining in state 1 (state 2) is almost unity, and it is only for larger negative values of $\Delta z_{m,t}$ that p_{11} (p_{11}) falls. However, the probability of remaining in state 2 (state 1) increase as $\Delta z_{m,t}$ increases.

On the other hand, when θ_1 and θ_2 ($\eta_1$and η_2) have statistically significant opposite signs, it may suggest that interest rates tend to decrease during a bull market (bear market). These results are given for the Czech Republic, Malaysia and the US in state 1 and Korea and Turkey in state 2 at a 10 per cent level of confidence (A visual illustration of these observations is given in Appendix F).

However, identical signs for both θ_2 and η_2 suggest that the transition probabilities, p_{11} and p_{22}, fluctuate in the opposite direction to which $\Delta z_{m,t}$ moves. In other words, identical signs for both θ_2 and η_2 may reflect a decrease in interest rate simultaneous with a bear market and an increase in interest rate simultaneous with a bull market. For example, when $\theta_2 < 0$, a positive shock to $\Delta z_{m,t}$ implies that the probability of remaining in state 1 increases in the next period since both p_{11} and $1 - p_{22}$ increase. These results are best shown for Korea and Turkey at a 10 per cent level of confidence, which implies that the interest rate decreases in a bear market and increases in a bull market (Panel B of Table 4.3).[67] Such a change is consistence with macroeconomic influence (Filardo, 1994; Henry, 2009).

[67] The opposite results have been found for the US.

The observations in this section provide mixed results regarding the effect of short-term interest rates on international equity markets. While changes in the short-term interest rate do not have significant effects in some emerging economies (e.g., Egypt, Hungary, Peru, Russia, Qatar, Thailand and the UAE), other markets show the opposite effect to what we have found for the US market (e.g., Turkey and Korea). Moreover, the economic significance of time variation in the short-term interest rate is more pronounced in one state while it is not significant in the other state. For example, Colombia, Greece and Poland show the same effect as the US in state 2 (bear market), that the interest rate increases in a bear market. However, Chile, India, Indonesia, Korea, the Philippines, Taiwan and Turkey show the opposite effect to the US in state 1 (bull market), that the interest rate decreases in a bull market.

The results of the null hypothesis test of no switching in equity markets against an alternative are presented in Panel C of Table 4.3. The results of the Wald test for the restrictions of two different levels of systematic risk, $h_0\colon \beta_1 = \beta_2$, are rejected at 5 per cent level of confidence for China, Colombia, Czech Republic, Greece, Hungary, India, Mexico, Peru, Russia, Qatar and UAE, giving evidence for the existence of switching behaviour in systematic risk. The results of the Wald test for restrictions of two different levels of volatility, $h_0\colon \sigma_1 = \sigma_2$, are rejected at a 5 per cent level of confidence for all of the equity markets except Mexico, giving evidence of volatility clustering in these markets. Also, the null hypothesis of FTP, $h_0\colon \theta_2 = \eta_2 = 0$, is rejected at a 10 per cent level of confidence for Brazil, Greece, India, Indonesia, Korea, Malaysia, South Africa, Taiwan, Turkey and the US, providing evidence for the state-dependent response of these markets to changes in the US money market.

Panel B of Table 4.4 shows that changes in the five-year bond level have a quite different effect on emerging equity markets. For example, now θ_1 and θ_2 ($\eta_1$and η_2) have statistically significant identical signs for Egypt in both states, Brazil, Chile, Hungary, India, Indonesia, Korea, Malaysia, Poland, Russia, Taiwan and the US in state 1, and Greece and Mexico in state 2 at a 10 per cent level of confidence. These results suggest that the five-year bond tends to increase (decrease) during a bull market (bear market). When θ_1 and θ_2 ($\eta_1$and η_2) have statistically significant opposite signs, it suggests that interest rate tends to decrease (increase) during a bull market (bear market). These results are given for Colombia, Greece, the Philippines and Qatar in state 1, and China, Colombia, Mexico, Russia, and South Africa in state 2 at a 10 per cent level of confidence (a visual illustration of these observations are given in Appendix G). These results are consistent with Yang and Hamori (2014), who find that

ASEAN equity markets are more affected by the US fund rate during a market expansion (bull market) than during a market downturn (bear market).

Further, when $\theta_2 > 0$ ($\eta_2 > 0$), a positive (negative) shock to $\Delta z_{m,t}$ implies that the probability of remaining in state 1 increases in the next period (the probability of remaining in state 2 increases in the next period). These results are best shown for Brazil, China, Russia and South Africa in both states at a 10 per cent level of confidence, which implies that the interest rate decreases in a bear market and increases in a bull market. We also observe both θ_2 and $\eta_2 < 0$ for Greece at a 10 per cent level of confidence, which implies that the interest rate increases in a bear market and decreases in a bull market (Panel B of Table 4.3).

The results of testing the null hypothesis of no switching in equity markets against an alternative are presented in Panel C of Table 4.4. The results of the Wald test for the restrictions of two different level of systematic risk, $h_0: \beta_1 = \beta_2$, are rejected at a 5 per cent level of confidence for all the equity markets, giving evidence for the existence of switching behaviour in systematic risk. Further, the results of Wald test for the restrictions of two different level of volatility, $h_0: \sigma_1 = \sigma_2$, are rejected at a 5 per cent level of confidence for all the equity market, giving evidence for volatility clustering in these markets. The null hypothesis of FTP, $h_0: \theta_2 = \eta_2 = 0$, is also rejected at a 10 per cent level of confidence for Brazil, Chile, Colombia, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Poland, Russia, Qatar, Taiwan and the US, providing evidence for the state-dependent response of these markets to changes in the US money market.

4.4.5 Comparison of Fit and Residual Diagnostics

In this section, we compare the fit of the SD International CAPM, where volatility is driven by the US short-term rate (time-varying transition probability) with the model used in Chapter 3 where volatility was driven by market risk premium (fixed transition probabilities). The results are reported in Table 4.5. According to the value of AIC, the average fit of the SD International CAPM (TVTP) for both the short-term rate and the five-year bond and SD International CAPM (FTP) is almost at the same level (-4.25). Likewise, the same results are observed for SC and HQ. However, the value of log likelihood marginally improved from 1677 to 1989 for the SD International CAPM (FTP) and 1695 for the SD International CAPM (TVTP) with the short-term rate and five-year bond respectively.

We also test properties of the SD International CAPM's residuals by applying Ljung–Box Q test statistics (Ljung & Box, 1978) for up to lag 4. The results presented in Table 4.6 show only the presence of serial correlation for Brazil, Colombia, South Korea and the US markets, similar to the results presented in Chapter 3.

4.4.6 Does Modelling Market Phases as Determined by Interest Rates Better Explain the Expected Returns?

The visual performance of the state-dependent International CAPM (TVTP) is depicted in Figure 4.5. by plotting the fitted expected returns, computed using the estimated parameter values in each model specification, against the realized average excess returns. If the SD International CAPM showed a useful qualitative prediction for the variation of equity returns, then we should see points spread along the 45-degree line. The fitted excess returns estimated by the SD International CAPM marginally improve across the two states, with the correlation slightly increased from 0.51 for the SD International CAPM (the right scatter plot of Figure 3.4) to 0.59 and 0.58 for the SD International CAPM (TVTP) with short-term rate and five-year bond respectively.

Table 4.5 Model fitting for SD International CAPM - TVTP

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
SD International CAPM (TVTP) - 3-month T-bill												
Log Likelihood	1648.67	1926.80	1772.51	1647.48	1724.73	1501.85	1423.39	1535.71	1721.33	1539.52	1729.24	2046.04
AIC	-4.05	-4.74	-4.36	-4.05	-4.24	-3.69	-3.49	-3.77	-4.23	-3.78	-4.25	-5.03
HQ	-4.03	-4.72	-4.33	-4.03	-4.22	-3.67	-3.47	-3.75	-4.21	-3.76	-4.23	-5.01
SC	-3.99	-4.68	-4.30	-3.99	-4.18	-3.63	-3.44	-3.71	-4.17	-3.72	-4.19	-4.98
SD International CAPM (TVTP) - 5-year T-bond												
Log Likelihood	1646.74	1928.58	1773.50	1650.78	1724.71	1507.42	1423.10	1538.89	1719.41	1538.85	1728.30	2050.29
AIC	-4.05	-4.74	-4.36	-4.06	-4.24	-3.70	-3.49	-3.78	-4.23	-3.78	-4.25	-5.04
HQ	-4.02	-4.72	-4.34	-4.03	-4.22	-3.68	-3.47	-3.76	-4.20	-3.76	-4.23	-5.02
SC	-3.99	-4.69	-4.30	-4.00	-4.18	-3.64	-3.44	-3.72	-4.17	-3.72	-4.19	-4.99

Table 4.5 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thai-land	Turkey	UAE	USA
SD International CAPM (TVTP) - 3-month T-bill												
Log Likelihood	1973.41	1656.78	1709.90	1663.77	1522.69	1254.51	1810.72	1852.89	1676.04	1337.50	1091.45	2778.87
AIC	-4.85	-4.07	-4.20	-4.09	-3.74	-4.31	-4.45	-4.56	-4.12	-3.28	-3.74	-6.85
HQ	-4.83	-4.05	-4.18	-4.07	-3.72	-4.28	-4.43	-4.53	-4.10	-3.26	-3.71	-6.82
SC	-4.80	-4.01	-4.14	-4.03	-3.68	-4.23	-4.39	-4.50	-4.06	-3.22	-3.67	-6.79
SD International CAPM (TVTP) - 5-year T-bond												
Log Likelihood	1975.06	1668.35	1705.91	1665.57	1527.42	1255.52	1813.06	1855.82	1677.06	1336.50	1091.49	2778.77
AIC	-4.86	-4.10	-4.19	-4.09	-3.75	-4.31	-4.46	-4.56	-4.12	-3.28	-3.74	-6.84
HQ	-4.84	-4.08	-4.17	-4.07	-3.73	-4.28	-4.44	-4.54	-4.10	-3.26	-3.71	-6.82
SC	-4.80	-4.04	-4.13	-4.03	-3.69	-4.23	-4.40	-4.51	-4.06	-3.22	-3.67	-6.79

Table 4.6 Residual diagnostic test for SD International CAPM with time-varying transition probability

	Brazil	Chile	China	Colombia	Czech Republic	Egypt	Greece	Hungary	India	Indonesia	Korea	Malaysia
SD International CAPM - IR												
Lag 2	-0.017***	0.001	-0.016	0.102***	0.022	0.052	0.016	0.000	0.011	-0.012	-0.214***	0.031
Lag 3	0.1***	-0.020	0.056	0.051***	-0.004	-0.011	-0.006	0.006	0.019	0.041	0.043***	-0.020
Lag 4	-0.004***	0.018	-0.003	0.042***	-0.032	-0.014	-0.014	0.027	-0.046	0.074*	0.075***	0.004

Table 4.6 continued

	Mexico	Peru	Philippines	Poland	Russia	Qatar	South Africa	Taiwan	Thailand	Turkey	UAE	USA
SD International CAPM - IR												
Lag 2	0.025	0.048	-0.017	0.009	0.005	0.020	0.030	-0.044	0.023	-0.005	0.013	-0.063*
Lag 3	0.032	0.052	0.012	-0.044	-0.005	-0.005	0.029	-0.026	0.003	0.007	-0.006	0.035
Lag 4	-0.026	-0.041	0.009	-0.068	0.036	0.093	-0.061	-0.015	0.021	-0.012	0.008	0.039

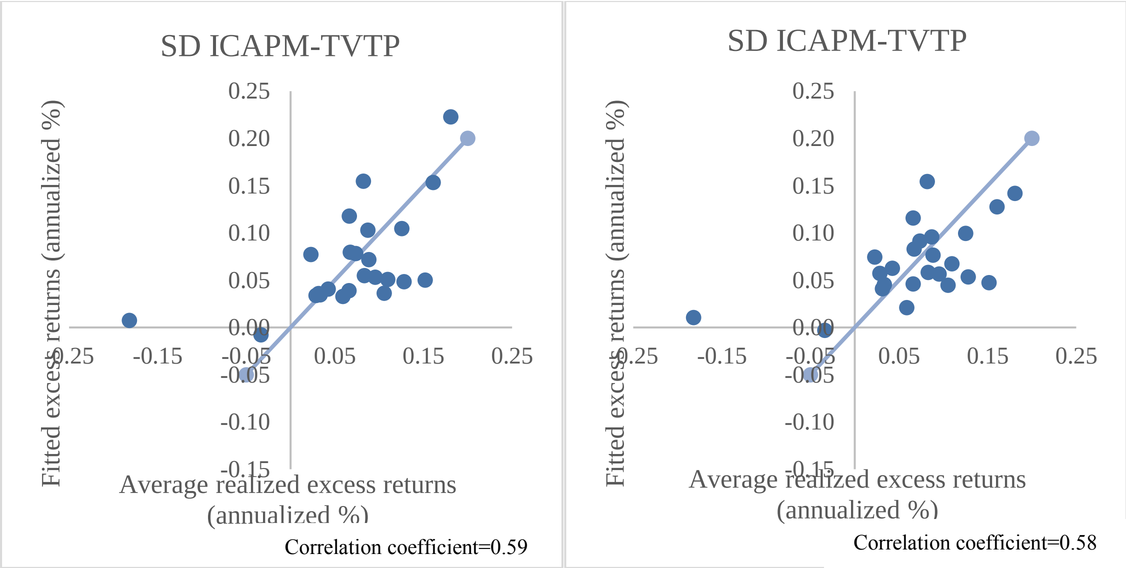


Figure 4.5 SD International CAPM (TVTP) fitted excess returns versus average realized excess returns for emerging market indices

These scatter plots depict points of the average realized excess returns versus the fitted excess returns estimated by the state-dependent International CAPM (TVTP) in equation (4.2). The right (left) scatter plot is when the 3-month US T-bill (5-year bond) is used to determine TVTP. The fitted excess returns are computed as a product of estimated betas in the previous period state and realized market excess returns for observation with smoothed probabilities of high market volatility being lower (higher) than 0.5. The straight lines on the graphs are 45-degree lines from the origins. The returns are computed as annualized.

4.5 Conclusion

The empirical presented in this chapter contributes to the body of research on asset pricing models by undertaking a robust analysis of returns with time-varying behaviour in emerging equity markets. It also adds further knowledge to the study of asset pricing models by incorporating the effect of US monetary policy on emerging equity returns. The model can be widely applied by portfolio managers when dealing with the asset allocation decision, for example by using an economic variable as a unique risk factor to determine the changes in time-varying returns in international equity markets rather than country-specific factors.

The purpose of this chapter was to examine the impact of US monetary policy on emerging equity markets, by considering two economic indicators as the key drivers of volatility in these regions in addition to the market risk premium. This chapter also tests whether an asset pricing model that derives volatility from an economic indicator better explains market return behaviour in emerging economies.

While the findings of this chapter provide marginal improvement in terms of model fitness compared to the models in Chapter 3, this chapter adds further knowledge to the determination of volatility in emerging markets; the results show that most of these markets display evidence of two market phases that are associated with changes in the US interest rate level. One market phase corresponds to a high-mean, low-variance phase where most of the equity markets respond to changes in the five-year US bond. This market phase is the dominant phase and persists for about 31 weeks on average. The other market phase is a low-mean, high-variance phase within which the equity returns respond less to news about the five-year bond. This estimated duration for this market phase is about 13 weeks on average.

Chapter 5 The Dynamic Allocation of Funds in Diverse Financial Markets Using a State-dependent Strategy: Application to Developed and Emerging Equity Markets

5.1 Introduction

Investors are aware that markets may undergo dramatic shifts. This behaviour may be related to market phases, and from time to time may start with a crisis that causes the markets to move from stable to uncertain conditions.[68] The potential always exists for future crises and the challenge for managers is to insulate their portfolios against future market downturns.

As discussed in Chapters 1 and 2, there are two main diversification benefits of investing in emerging economies. First, the higher expected returns make these markets an attractive investment opportunity from the viewpoint of international investors (Bekaert & Harvey, 1995; Bodie et al., 2013). Second, although the liberalization process has increased the correlation of emerging markets, causing the risk reduction benefit of diversification to diminish, these markets are still not fully integrated with world capital markets (Bekaert, Harvey, Lundblad, & Siegel, 2011) . This incomplete degree of integration with world capital markets, along with their potential for higher returns, provides potentially attractive investment opportunities.

Changes in the behaviour of financial markets present significant challenges for both risk management and portfolio selection. As discussed earlier, international financial markets are more highly correlated with each other in bad times than in normal times (Junior & Franca, 2012; Longin & Solnik, 2001), and this changing correlation will impact on mean-variance portfolio optimization when markets decline.[69] The ability of an SDMM to accommodate changing correlation provides a means of implementing portfolio optimization in declining markets (Ang & Bekaert, 2002a).

This chapter extends the prior research on this aspect of market correlation by demonstrating how the concept of state-dependent correlation of emerging markets with developed markets can be used to develop an optimal asset allocation strategy. The aim is to accommodate the

[68] Evidence of such behaviour has been reported for stock returns (Hamilton & Susmel, 1994), interest rates (Gray, 1996), inflation (Kumar & Okimoto, 2007) and commodity prices (Heaney, 2006).
[69] As stated by Hamilton and Susmel (1994) "extremely large shocks arise from quite different causes and have different consequences for subsequent volatility than do small shocks". From the econometric point of view, large shocks in financial markets increase the covariance between assets and this high volatility causes high correlation between financial markets during bad times. This asymmetric correlation leads to poor estimates when we use historical data to make optimal decisions.

switching behaviour of financial markets using an SDMM that allows the asset allocation decision to be dependent on an identified state. To this end, we address the following questions: Does incorporating market phases enhance asset allocation strategy? Can asset-allocation strategy be improved by allowing the interest rate, in addition to time-varying volatility in equity risk premium, to identify the market phase?

The SDMM, introduced Goldfeld and Quandt (1973) and later popularized by Hamilton (1989), allows data to be drawn from different distributions (states) where the process is modelled by the probability of switching between different states. Based on market return volatility, a degree of likelihood that the process will either remain in the same state or transition to another state in the next period is assigned.

SDMMs have stimulated interest in international asset allocation decisions and portfolio selection. The SDMM may be superior to other models commonly used in the asset allocation decision, as it gives useful information about the prevailing state during different time horizons and this information can convert the static mean-variance model into a dynamic model enabling optimal decisions in portfolio selection. Because investors give different weights to various asset classes depending on which state the market is in, this will change the optimal asset allocation during different time horizons. This characteristic of the model enables investors and portfolio managers firstly to hedge against risk during bad times by investing in safer asset classes such as cash and bonds, and secondly to make optimal allocation decisions during normal times by diversifying the portfolio across asset classes.

Ang and Bekaert (2004), using six international equity indices, document how the presence of state-dependency in normal and bear markets can be used in global asset allocation settings. Their model allows the estimation of the expected return vector and the covariance matrix of the portfolio returns for each state. More precisely, the expected returns of the indices in the portfolio are assumed to be stochastically distributed from multiple distributions based on two identified states, which are the two states in this study. Ang and Bekaert (2004) find that state-dependent strategy can potentially outperform the static mean-variance approach because it can capture the different distribution of portfolio returns during different market phases. However, they point out that the outperformance of a state-dependent strategy may be related to a historical period (in their case 1975–2000). Moreover, they indicate that the state-dependent portfolio need not be home biased, and in any practical application of an SDMM, the optimal portfolio is likely to be more internationally diversified.

Previous research in relation to the merits of a state-dependent strategy in emerging markets is thin. In this study, we construct a portfolio that includes the emerging as well as developed equity indices by applying SDMM. we follow Ang and Bekaert's (2004) approach that analyses the asset allocation strategy for developed equity markets, extending their approach to developed and emerging equity markets.

we find that emerging markets are characterized by different distributions of returns in different market phases relative to world equity markets: a high variance phase with lower expected returns and a low variance phase with higher expected returns. This is consistent with my initial belief that the presence of two states and two optimal tangency portfolios is superior to a single unconditional optimal portfolio. After accounting for transaction costs, the Sharpe ratio increases from 0.55 to 0.75 by holding the optimal tangency portfolio with state-dependent strategy in an out-of-sample portfolio. In other words, investors can optimize the returns on their investment by diversifying their portfolio towards emerging markets (i.e. emerging Asia and emerging Europe).

The remainder of this chapter is organized as follows. Section 2 reviews the previous literature. Section 3 describes data and Section 4 gives an overview on the methodology. Section 5 presents the empirical findings and compares the performance of state-dependent portfolios with that of the static mean-variance optimal portfolios. Section 6 carries out a practical implementation to check whether the results are robust in out-of-sample performance. Section 6 presents my concluding remarks.

5.2 Literature on the Dynamic Allocation of Funds under a State-dependant Approach

International diversification of investment portfolios and the allocation of funds across regions are crucial for investors. Grubel (1968) was one of the first researchers to investigate the benefits of international portfolio diversification and found that an internationally diversified equity portfolio brings higher returns and lower risks in comparison to a purely domestic equity portfolio.

Portfolio optimization is the most developed and practiced approach to assess the optimal decision in allocation of funds. The mean-variance approach developed by Markowitz (1952) is the foundation for portfolio selection. The method selects the optimal portfolio by calculating the risk-return trade-off utilizing the estimated mean vector and covariance matrix of portfolio returns. One of the benefits of the Markowitz approach is that there are no limitations on the asset classes that can be incorporated. However, the Markowitz approach is a one-period approach without stochastic specifications. The model also assumes that asset returns are formed in a stationary process with the mean and covariance matrices of returns being constant over a specific period.

A significant body of research argues that asset returns follow a more complex process, with multiple periods relating to changes in market conditions, each associated with a different distribution in returns – one subject to high volatility and low return and the other to low volatility and high return. The stochastic volatility present in asset returns may provide misleading information about asset performance and hence result in unfavourable asset allocation. This empirical characteristic of asset returns highlights the necessity for a dynamic model for use in deciding on the allocation of funds to account for different distributions of returns across different time horizons. In order to compensate for this non-linearity in asset returns, some studies use ARCH specification by allowing the error variance to be time varying and dependent on its previous values and previous level of error terms. A counterpart to ARCH-type model is the SDMM, which enables investors to characterize the asset returns with different possible distributions.

This thesis characterizes asset returns by two states where the first (second) state has the features of bull (bear) market with higher (lower) expected returns and lower (higher) variance. As these two market conditions offer different risk and returns opportunities, investors' asset allocation varies significantly depending on investors' realization about the underlying state probabilities.

The SDMM generates a practical measure for addressing the shifting correlation conditions. In this study, we follow the standard Markowitz portfolio approach but allow for the shifting nature of the covariance matrix under separate market situations. Indeed, one of the serious concerns that emerged during the 2008 Global Financial Crisis (GFC), and more broadly in any period of market turbulence, was the sudden increase in correlations that arise leading to an ensuing lack of diversification in investment portfolios.

There have been several studies detecting the presence of multiple states in financial markets, particularly in stock markets. A notable example is Hamilton and Susmel (1994), who apply a Markov-switching model by analysing US weekly stock returns to describe volatility in stock returns, where a high volatility state is related to economic conditions. Their analysis supports previous findings that negative shocks lead to higher volatility than would positive shocks of the same magnitude, which is known as asymmetric volatility.[70] These studies generally find that high (low) returns in the stock market are associated with low (high) volatility.

The increase in correlation between international financial markets, which has been observed during market downturns, raises questions about the advantage of international diversification in the determination of optimal portfolios. Ang and Bekaert (2002a) were among the first to address this issue by developing a dynamic portfolio selection for US investors utilizing a Markov-switching approach that could account for high correlation and volatilities during market turbulence. They show that international diversification can still benefit investors while allowing for state-dependency in international financial markets. They develop maximum likelihood estimates to distinguish between two states and estimate the mean vector and covariance matrix for the respective return series for each state.

A growing number of studies have since considered the concept of using a Markov-switching model in asset allocation decision (Ang & Bekaert, 2004; Bae et al., 2014; Dou et al., 2014; Graflund & Nilsson, 2003; Guidolin & Timmermann, 2007, 2008; Honda, 2003; Kritzman, Page, & Turkington, 2012; Nystrup et al., 2015; Nystrup, Madsen, & Lindström, 2018; Pereiro & González-Rozada, 2015; Tu, 2010). In these studies, the market is generally characterized as having two (Ang & Bekaert, 2004) or more possible states (Guidolin & Timmermann, 2007; Kritzman et al., 2012) with well-determined distribution parameters and transition probabilities that assign the probability of remaining or switching to another state. They find that a state-dependent strategy is superior to a standard static mean-variance approach, as the model potentially captures different distributions of asset returns depending on the market condition.

Guidolin and Timmermann (2007) characterize the markets into four separate states which they designate as crash, slow growth, bull and recovery states using various asset classes, and study how optimal asset allocation decisions can change depending on the identified state based on different distributions of asset returns. They confirm the economic importance of accounting for the presence of state dependency in asset allocation decisions. More recently, Dou et al.

[70] Asymmetric volatility is a situation in which the volatility of a security is higher when the broader market is performing poorly than when it is performing well, whereas, volatility clustering refers to the observation that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes" (Mandelbrot, 1963).

(2014) implemented an SDMM based on region-sorted and sector-sorted equity indices portfolios. They find that state-dependent asset allocations outperform the traditional static asset allocation while optimal allocation across sector-sorted portfolios provides greater benefit compared to a region-sorted portfolio. More recently, (Nystrup et al., 2018) find that a Markov-switching asset allocation-based model outperforms buy-and-hold investment decisions after controlling for transaction costs.

Figure 5.1 illustrates the development of state-dependent asset allocation strategy since the publication of the first academic paper in this field. This thesis contributes to the asset allocation literature in two ways: firstly by extending the state-dependent asset allocation strategy to emerging equity markets based on the belief that the asymmetric correlation of these markets can still provide diversification benefits; and secondly, unlike previous studies, by investigating the switching behaviour of equity returns using lower frequency data, which may convey more timely information especially during the beginning of high variance states when the necessity of diversification is more pronounced. In addition, rather than having more than two states as in previous studies, we maintain the principle of parsimony and assume that there are two conditions characterized as bull and bear markets, since having more than two states may result in computational problems.

5.2.1 Risk Aversion

Some studies focus on specific constant relative risk aversion preferences in a state-dependent Markov framework. For instance, Graflund and Nilsson (2003) address the question of how investors' perceptions of the state of the economy affect the dynamic portfolio decision in four major markets (the US, UK, Germany and Japan) with a Markov-switching approach by utilizing a mixture of Gaussian distributions. Their findings pinpoint the economic influence of accounting for the presence of state dependency, as taking a specific state into account affects the portfolio decision.

Honda (2003) investigates the dynamic portfolio choice in which the mean returns of a risky asset depends on an unobservable state variable of the economy. The investor evaluates the prevailing state by observing past and current stock prices. Honda (2003) finds that the optimal portfolio of a long-term investment horizon can be essentially different from the optimal portfolio of a short-term investment horizon. Honda (2003) also finds that the level of investor risk aversion, the estimation of asset returns, and the prevailing state are key factors in the investor's optimal portfolio decision.

Figure 5.1 Literature review and chapter contributions

Mean-variance efficient portfolio (Markowitz, 1952)
International portfolio diversification in developed markets (Grubel, 1968)

SDMM is introduced by Goldfeld and Quandt (1973) popularized by Hamilton (1989) in economics.
Hamilton and Susmel (1994) add ARCH into the SDMM in stock market returns

Introduction of SDMM in asset allocation decision in equity markets (Ang & Bekaert, 2002a)

State-dependent market model and Risk aversion: (Bae, Kim, & Mulvey, 2014; Graflund & Nilsson, 2003; Honda, 2003)

Identify states using economic predictor:

Market risk premium and Interest rate (Ang & Bekaert, 2004)

Dividend yields (Guidolin & Timmermann, 2007)

Accounting for transaction costs

Detrimental to portfolio performance (Hess, 2006)

The model remains profitable (Bulla et al., 2011; Nystrup, Hansen, Madsen, & Lindström, 2015)

Data frequency: Most of the previous studies used monthly.

Daily (Bulla, Mergner, Bulla, Sesboüé, & Chesneau, 2011; Jiang, Liu, & Tse, 2015)

Markov model is more appropriate to be used on monthly or weekly data (Hamilton & Susmel, 1994)

Using different asset classes:

Bonds and stocks (Guidolin & Timmermann, 2007)

Stocks Fama and French 25 portfolios size and B/M (Tu, 2010)

Commodity index (Bae et al., 2014)

Regions and sectors (Dou, Gallagher, Schneider, & Walter, 2014)

Gap (1): The practical tests have been limited to developed markets focusing on different asset classes. These markets are integrated therefore dynamic asset allocation between diversified asset may not be successful.

Gap (2): Most studies use monthly returns.

Contribution (1): Extend the SDMM to broader international markets (i.e. emerging markets)

Contribution (2): Investigate the profitability of SDMM on weekly basis, which may convey more timely information especially during the beginning of high variance states when necessity of diversification is more pronounced

Contribution (3): Using SDMM to estimate expected returns both with FTP and TVTP

Contribution (4): Accounting for transaction costs to test whether the strategy remains profitable.

Bae et al. (2014) develop a stochastic program to optimize portfolio selection employing the Markov-switching approach. Their analysis confirms the findings of earlier researchers that accounting for state-dependency information helps portfolios to minimize risk during left-tail events. Unlike these studies, which used sophisticated statistical techniques to solve portfolio choices, the approach adopted in this thesis is to maintain a practical model for both individual and institutional investors.

5.2.2 Economic Predictors

By contrast, some studies seek to solve the portfolio choice problem by using an economic predictor with a time-varying investment opportunity in SDMM to identify the state probabilities. For example, Ang and Bekaert (2004) use a two-state Markov-switching model in the context of an optimal international equity portfolio. They find that substantial wealth was achieved when investors switched to cash in a persistent high-volatility state because high volatility states are contemporaneous with periods of higher interest rates.[71] However, their findings are related to a specific period in time (1975–2000) and using a different dataset may yield a different conclusion.

Guidolin and Timmermann (2007) use three major asset classes, stocks, bonds and cash from a US investor's perspective, and use the dividend yield to identify state probabilities and predict asset returns. They show that optimal allocation of funds varies significantly across different states and changes over time as investors reassess their estimates of the state probabilities, where each state has an intuitive interpretation. The out-of-sample forecasting method conducted in their study supports an economic justification for the consideration of state-dependence in the allocation of funds.

Kritzman et al. (2012) apply Markov-switching models using economic variables to forecast asset returns in phases of market turbulence, inflation and economic growth. They find that state-dependent asset allocation substantially improves portfolio performance in comparison to static asset allocation. Using an economic predictor/exogenous variable may be more appropriate when dealing with asset allocation in a specific country or region. In this study, however, the portfolio consists of the universe of emerging and developed markets. In the first section of this chapter, the market risk premium determines which state the market is while in this

[71] They stated that "in a persistent high-volatility market, the model told the investor to switch primarily to cash. Large market-timing benefits are possible because high-volatility states tend to coincide with periods of relatively high interest rate".

section, the short-term interest rate predicts transitions between states and thus, it indicates time variation in expected returns.

5.2.3 Transaction Costs

Investors should consider the benefit of dynamic asset allocation with caution, because not all previous studies consider the transaction costs involved in switching between different assets (Ang & Bekaert, 2004; Graflund & Nilsson, 2003; Guidolin & Timmermann, 2007, 2008). Accounting for transaction costs is essential as the cost of frequent rebalancing arising from explicit transaction costs such as brokerage and taxes, and implicit costs such as bid-ask spreads, can outweigh the benefits of a dynamic investment strategy. Hess (2006) finds that adjusting for transaction costs in each period reveals detrimental effects on portfolio performance and causes the advantage of using an SDMM to disappear.

Conversely, Bulla et al. (2011) find that the model remains profitable after considering transaction costs. Nystrup et al. (2015) also examines whether a state-dependent investment strategy can effectively respond to changes in financial markets, to benefit over the long-term horizon investment in comparison to standard approaches. They confirm the validity of their investment strategy of switching between stocks and bonds and conclude that even with the inclusion of some level of transaction costs, the dynamic investment strategy can be profitable. Following Bulla et al. (2011), this chapter also accounts for transaction costs to test whether the strategy remains profitable.

5.2.4 Using Different Asset Classes

Tu (2010) suggests a Bayesian framework for constructing a portfolio that considers the state-dependent model together with asset pricing model uncertainty and parameter uncertainty. The sample data consists of investable assets including the risk-free asset, the value-weighted Centre for Research in Security Prices market index portfolio, the size factor portfolio, the value factor portfolio and Fama and French portfolios sorted by size and book-to-market. Findings reveal that the economic value of accounting for a state-dependent model is substantially different from the commonly used single-state models and suggests it should be considered instead in portfolio selection, regardless of any concerns about model or parameters estimates.

Bae et al. (2014) investigate the presence of state dependency using the commodities index as an additional asset class to equity and bonds. More recently Dou et al. (2014) extend Ang and

Bekaert's (2004) approach to a diverse range of regions and sectors. They find that state-dependent allocation of funds adds value to the standard optimal portfolio, supporting the prior findings by other researchers. Additionally, diversification across sectors to achieve an optimal allocation provides an alternative to international diversification across markets. In addition, Jiang et al. (2015) test a dynamic investment strategy by applying a Markov-switching approach using the international iShares exchange-traded funds. They find that a dynamic investment strategy outperforms the standard mean-variance strategy, and this can be more practical and even applied to frequently traded funds such as exchange-traded funds.

5.2.5 Extension of the SDMM to International Markets

While many studies focus on different asset classes in developed markets primarily from US investors' viewpoint, there is little work that extends the Markov-switching approach to a broader international asset allocation strategy. For instance, Pereiro and González-Rozada (2015) use a state-dependent model known as the self-exciting threshold autoregressive model, to identify price changes in a large number of emerging and developed markets. They show that such a model has the potential to improve the accuracy of the long-term financial forecast. However, they do not check whether taking state-dependence into account can adequately optimize asset allocation programme.

One conclusion from these findings is that the potential benefit of state-dependent based asset allocation is achievable, provided there is sufficient information about the prevailing state and future changes. For instance, Ang and Timmermann (2011) survey the finance literature on the application of state-dependent models to interest rates, equity returns, exchange rates and asset allocation. They conclude that switching behavior in financial markets leads to potentially significant consequences for investors' optimal portfolio selection. However, the practical tests on a dynamic investment strategy have been limited to relatively developed financial markets by focusing on different asset classes such as cash, bonds and equities. As these markets are relatively integrated, the dynamic asset allocation that switches between diversified assets in these markets may not purely reflect the success that can be achieved by investors, especially during bad times. The first contribution of this part of the thesis is to investigate whether the SDMM model is profitable when investors switch their funds to emerging markets as an alternative asset class in comparison to investing in a safer asset class such as cash or bonds during bad times.

5.2.6 Data Frequency

Most of the previous studies on state-dependent asset allocation strategies use monthly returns data, but there a few studies that investigate the profitability of dynamic asset allocation strategies on daily returns (Bulla et al., 2011; Jiang et al., 2015). Hamilton and Susmel (1994) assert that low-frequency data such as weekly and monthly data are more appropriate for state-dependent models. Consequently, the second contribution of this chapter is to investigate the profitability of dynamic asset allocation by using weekly equity returns. Using weekly returns has two advantages; first, it avoids the problem of noise in daily or tick data that makes it difficult to isolate cyclical variation in high-frequency data. Investigating the switching behaviour of asset returns on higher frequency data such as weekly data may convey more timely information, especially during the beginning of the high volatility state when the necessity of diversification is more critical (Dou et al., 2014). On the other hand, it will be interesting to see whether using weekly data will bring another pattern of asset returns into play when SDMM is applied.

5.3 Data

The portfolio set consists of equity total return indices for emerging market regions (Asia, Europe and Latin America) and developed markets (Europe, North America and the Pacific) as reported by MSCI. The MSCI indexes constitute a reliable benchmark measure of market performance and have been used in prior similar studies (Ang & Bekaert, 2002a, 2004; Dou et al., 2014; Guidolin & Timmermann, 2008). Table 5.1 lists the composition of international equity markets include in each index.

Weekly returns data from 3 January 2001 till 30 December 2015 is obtained from Thomson Reuters Financial DataStream. Weekly data is used to avoid the problem of non-synchronous trading and possible short-term correlations due to noise with higher frequencies such as daily data.[72] Using weekly data also helps with better identification of cyclical behaviour[73] and analysis of state dependency across time. In addition, Hamilton and Susmel (1994) suggest that

[72] Nonsynchronous trading can cause correlations between two independent assets when there are none. This in turns affects portfolios and risk management.

[73] Financial time series often show medium-term falls and rises, which usually repeat in cycle, which refers to cyclical behaviour. Cyclical behaviours in equity returns are widely identified in the finance literature, particularly in bull and bear market phases (Chen, 2009; Edwards, Biscarri, & De Gracia, 2003; Gonzalez, Powell, Shi, & Wilson, 2005; Granger & Silvapulle, 2002). Cyclical behaviour is different from seasonal behaviour, in which the

state-dependent heteroskedasticity is more appropriate for low-frequency data such as weekly and monthly data. Moreover, according to Aloui and Jammazi (2009), state dependency can be detected more clearly across time using low frequency data. Further evidence is proved by Walid et al. (2011), who employ an SDMM to investigate the dynamic linkage between stock price volatility and exchange rate changes in emerging markets. In addition, most of the previous studies on state-dependent asset allocation strategy use monthly returns data; as recommended by Dou et al. (2014), one extension of which would be to investigate the switching behaviour of asset returns on a weekly basis, which might convey more timely information, especially during the beginning of the high volatility state when the necessity of diversification is more highlighted. This chapter applies the SDMM to investigate switching behaviour in weekly data.

Table 5.1 Composition of international equity markets

The developed and emerging equity markets in each region based on MSCI equity market classification.

Americas		Europe		Asia-Pacific	
Emerging	Developed	Emerging	Developed	Emerging	Developed
Brazil	US	Czech Republic	Austria	China	Australia
Chile	Canada	Greece	Belgium	India	Hong Kong
Colombia		Hungary	Denmark	Indonesia	Japan
Mexico		Poland	Finland	Korea	New Zealand
Peru		Russia	France	Malaysia	Singapore
		Turkey	Germany	Philippines	
			Ireland	Taiwan	
			Italy	Thailand	
			the Netherlands		
			Norway		
			Portugal		
			Spain		
			Sweden		
			Switzerland		
			the UK		

Returns are calculated as the natural log of total returns on the indices. The weekly 3-month US T-bill is used as the proxy for the risk-free rate. For the world financial markets index, we

fluctuations are fixed, associated with a specific event, and short-term. Using weekly returns enables us to distinguish between these two returns behaviours and identified the market phases rather than the seasonal effects, which usually observed in higher frequency data.

use the MSCI world total return index. These rates are used to evaluate the performance of equity indexes by applying the International MM (Market Model).

Table 5.2 Panel A presents the summary statistics of a sample set. The first part summarizes characteristics of the excess return series for each of the equity regions. The following properties of data are notable. First, markets with marginal excess returns do not necessarily present higher volatility, suggesting that the risk-return trade-off may not be present as the expected returns do not rise with an increase in volatility, as indicated by standard deviation. Second, negative skew implies that the return distribution is skewed to the left, suggesting that large negative returns are most likely to happen, which is not surprising given that the sample contains episodes of large losses; however, the excess return distributions are not heavily unconditionally skewed, except for Latin America and emerging Europe. Third, as a common factor in financial time series, these markets exhibit high levels of kurtosis. Accordingly, the distributions of excess return series are leptokurtic and hence non-Gaussian.

Jarque-Bera test statistics indicate that excess return series are not well estimated by the normal distribution. The episodes of high and low variance present in the distributions of returns provide motivation for the application of the SDMM. We perform the unit root test of Dickey and Fuller (1981) on the logarithm of excess returns. The associated test statistics are also presented in Table 5.2 Panel B. The results show that all of the excess return series are integrated to the order of 1, since the results of the ADF test statistics are less than critical value. Estimates from the correlation matrix of excess return series (Table 5.2 Panel C) for the world markets and the six equity regions suggest that the excess returns series have very different degrees of correlation, with correlation coefficients ranging from 0.75 to 0.94 for emerging Asia and Europe respectively.

Table 5.2 Descriptive statistics on weekly excess returns

Panel A, reports summary statistics of weekly excess returns and are denominated in US dollars. The returns are in excess of, for each region, 3-month US T-bill rates from the logarithmic rate of total return as weekly frequency. The sample period for regional returns is from 3 January 2001 to 25 December 2015. ADF in Panel B stands for Augmented Dickey-Fuller unit root test statistics. The ADF test for all the log of returns are significant at 1 per cent level. The correlation matrix of excess return series for the world markets and the regional markets reports in Panel C.

		World	Emerging Asia	Pacific	Emerging Europe	Europe	Emerging Latin America	North America
A.	Sample moments							
	Mean	0.0005	0.0014	0.0003	0.0009	0.0005	0.0012	0.0006
	Maximum	0.0902	0.2030	0.1400	0.2066	0.1051	0.1077	0.1027
	Minimum	-0.1751	-0.1874	-0.1725	-0.3762	-0.1558	-0.4041	-0.1698
	Standard deviation	0.0245	0.0326	0.0262	0.0455	0.0301	0.0391	0.0243
	Skewness	-0.8941	-0.4061	-0.5332	-1.3471	-0.6803	-1.7959	-0.7193
	Kurtosis	8.0501	7.3696	6.5301	12.3317	6.0909	17.7782	8.2908
	Jarque-Bera	936.37	644.45	443.65	3077.81	372.10	7546.05	980.76
B.	Unit root test							
	ADF (Log returns)	-5.89*	-9.06*	-5.97*	-8.99*	-10.88*	-6.06*	-6.28*
C.	Correlation matrix							
	EM Asia	0.7430						
	Pacific	0.7593	0.7533					
	EM Europe	0.7523	0.6876	0.6376				
	Europe	0.9372	0.6825	0.6929	0.7343			
	EM Latin America	0.7996	0.6849	0.6240	0.7816	0.7447		
	North America	0.9457	0.5926	0.5918	0.6318	0.8121	0.7166	

Figure 5.2 plots the volatility clustering of logarithmic excess returns. Some of these equity markets experience spikes of volatility at similar times during world events such as the 2001 September 11 terrorist attack, the 2003 Internet bubble, the 2008–2009 GFC and the more recent market fall due to the European sovereign debt crisis in 2011.

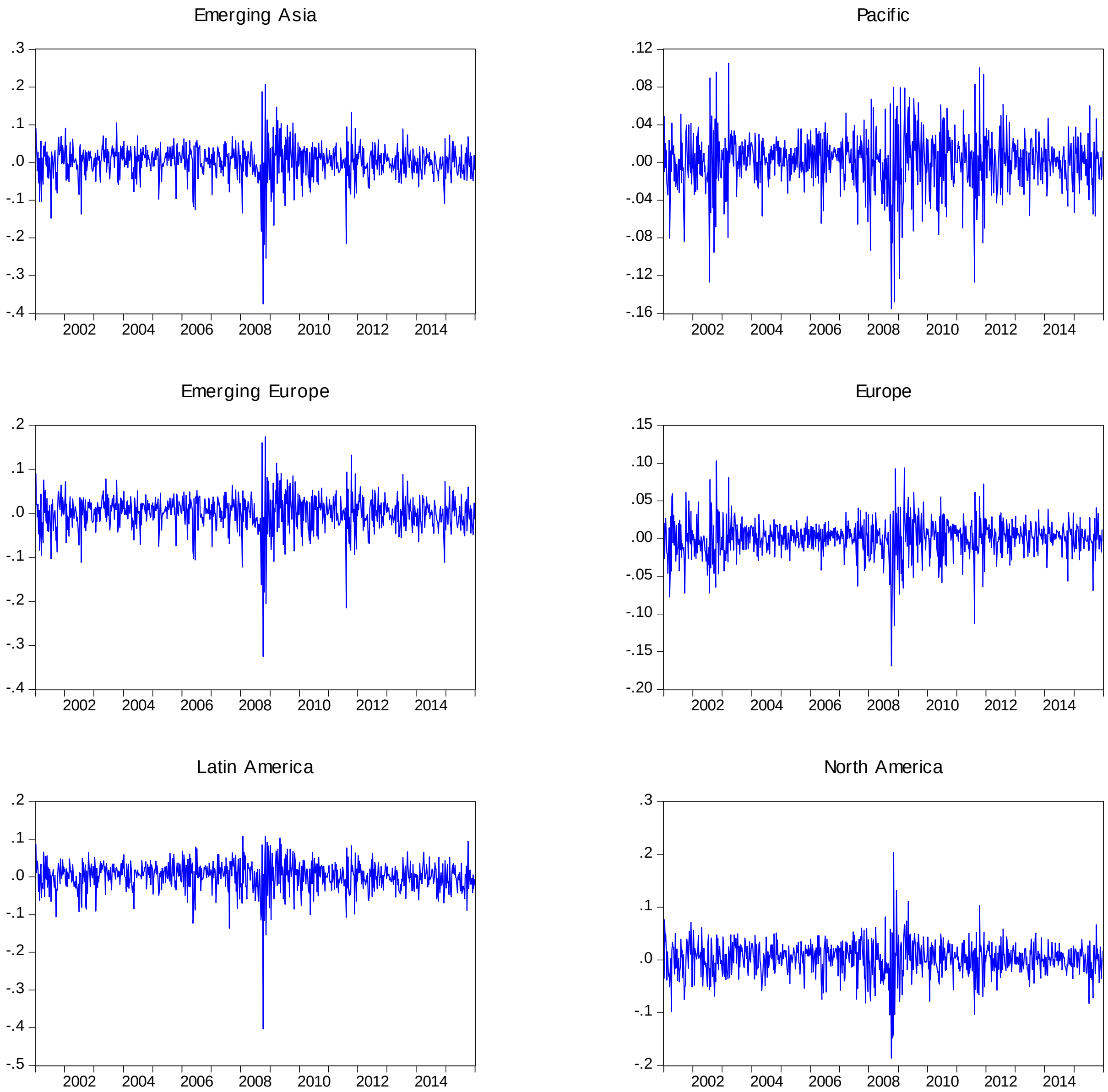


Figure 5.2 Plot of logarithmic excess returns, showing volatility clustering for developed and emerging equity regions.

5.4 Description of the Model

The parameter estimation of the SDMM consists of two steps. The first is the estimation of the state-dependent expected returns and standard deviation of the world market returns. From that, it is possible to distinguish between high volatility and low volatility in the world market based on the realization of the state probabilities, including both ex-ante and ex-post probabilities.

The second step is the estimation of the expected excess returns for each region based on the identified state of the world market returns but separate from the estimation of the world return parameters. Hence, the information in individual regions does not influence the world return generating process.

5.4.1 State-dependent Model – World Market Returns

The theoretical idea underlying the SDMM is that there exist two states of the economy, the high volatility state which is associated with lower expected returns and the low volatility state which is associated with higher expected returns. Previous studies show that during the normal period, higher returns with low volatility are observed and during periods of uncertainty lower returns with high volatility are observed. In other words, the first state corresponds to the normal period (high return – low volatility) and the second state is related to the period of uncertainty (low return – high volatility).[74] These two states may offer different investment opportunities and hence different asset allocations over time as the investors' perceptions change depending on the underlying state probabilities. This thesis investigates whether a state-dependent mean-variance efficient (MVE) portfolio across different states can potentially outperform the mean-variance optimal portfolio. To demonstrate this hypothesis empirically, the excess return series is set in a state-dependent framework. To maintain the parsimony of the model, the Ang and Bekaert (2004) approach is followed, where it is assumed that the expected excess returns in each region are linear to its beta with respect to the world market returns. In other words, we assume that the expected excess return for each region is driven by the world expected excess return based on market volatility. The equation for the world equity market in excess of the risk-free rate is then defined as:

$$r_t^w = \mu_{s_t}^w + \sigma_{s_t}^w \varepsilon_t^w \tag{5.1}$$

Where $\mu_{s_t}^w$ is the world conditional expected return and $\sigma_{s_t}^w$ is the world conditional variance (volatility). The assumption is that the world expected returns and volatility could take two different values depending on the realization of the two unobserved state variables, s_t, which

[74] Several studies have extended the model to more number of states, see for example Guidolin and Timmermann (2007). Following Ang and Bekaert (2004), we limit our analysis to two states for several reasons: first, to maintain the parsimony of the model, we assume that markets are characterized by two states; since having more than two states may result in computational problems. Second, in Chapter 4, we tested the goodness of fit of a two-state versus a three-state model. we found that in the three-state model, the third state only accounted for high spikes and did not necessarily capture the state of the economy. This is consistent with Abdymomunov and Morley (2011) findings.

indicates the world market condition. Then we assume that the excess returns series have two unobserved states, state 1 and state 2. Subsequently, $\mu_{s_t}^{w}$ and $\sigma_{s_t}^{w}$ can take different values according to the realization of the state variable s_t. As a result, the equity markets can be defined by higher uncertainty with lower returns (bear market) and lower uncertainty with higher returns (bull market).

To complete this process, the likelihood function should be characterized so as to maximize the parameters of this function. In conducting an SDMM in this study, the parameters estimation is carried out by adopting the expectation maximisation (EM) algorithm of (Hamilton, 1990) (Appendix B for further explanation on the Expectation Maximisation Algorithm).

The state variable s_t follows a two-state Markov chain process with constant transition probabilities:

$$p_{ij} = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix} \tag{5. 2}$$

The probability of remaining in the same state next time depends only on the current state. If the current state is state 1, p_{11} denotes the probability of staying in the first state and $1 - p_{11}$ denotes the probability of transitioning to another state. Likewise, if the current state is State 2, p_{22} denotes the probability of remaining in State 2 and $1 - p_{22}$ denotes the probability of transitioning to another state (see Appendix A for further explanation of the Markov chain process).

With this alteration in the model, the world expected returns and volatility can vary through time. If an investor knows the current state, the conditional expected returns and conditional volatility for the world market returns in the next period would be:

$$e_1^{w} = p_{11}\mu_{s_t=1}^{w} + (1 - p_{11})\mu_{s_t=2}^{w} \tag{5.3}$$

$$\Sigma_1^{w} = p_{11}(\sigma_{s_t=1}^{w})^2 + (1 - p_{11})(\sigma_{s_t=2}^{w})^2 + p_{11}(1 - p_{11})\left[\mu_{s_t=2}^{w} - \mu_{s_t=1}^{w}\right]^2 \tag{5.4}$$

$$e_2^{w} = (1 - p_{22})\mu_{s_t=1}^{w} + p_{22}\mu_{s_t=2}^{w} \tag{5.5}$$

$$\Sigma_2^{w} = (1 - \mathrm{p}_{22})(\sigma_{s_t=1}^{w})^2 + p_{22}(\sigma_{s_t=2}^{w})^2 + p_{22}(1 - p_{22})\left[\mu_{s_t=2}^{w} - \mu_{s_t=1}^{w}\right]^2 \tag{5. 6}$$

If the current state is State 1, $s_t = 1$ and would be:

If the current state is State 2, $s_t = 2$.

e_1^w denotes the world conditional expected returns in state 1. If state 1 realizes, the investor assigns the expected returns to be e_1^w. Likewise, if the investor realizes that the world market is in state 2, the investor considers e_2^w to be the expected returns. To estimate these expected returns, the investor applies $(1 - p_{22})$ and p_{22} to weight the expected returns.

For instance, when the investor knows that the world market is in state 1 today, the expected return for the next period depends on the investor's expectations for the state realization at time $t + 1$. Therefore, the investor weights the possible realization of expected returns, $\mu_{s_t}^w$, based on related probabilities.

Like the conditional mean, the conditional variance changes across states. When the investor realizes that the world market is in state 1 at time t, the investor expects that the first state will carry on with probability p_{11} and assigns a probability of $(1 - p_{11})$ for transitioning to another state (i.e. state 2). The first element in equation (5.4) and equation (5.6) is a weighted average of the conditional variance across the two states. The second element is an additional jump, which arises because the conditional mean is different across the two states.

In the case that $p_{11} = 1 - p_{22}$, the assumption of state structure is not fitted to the expected returns since they are identical through different states. However, the empirical estimation of state persistence has been documented in previous studies (Ang & Bekaert, 2002a, 2004; Guidolin & Timmermann, 2008).

5.4.2 State-dependent Markov Model (Return Generating Function)

SDMM is considered the return generating function of the market model, where it is conditioned by state variable s_t which identifies the process based on the realization of the state probability at each point in time.[75] The underlying assumption is as follows: if $s_t = 1$ it means that the process is in state 1 and if we assume that $s_t = 2$, the process is in state 2. In other words, the return generating function can be modelled by an SDMM in which one state is subjected to normal volatility ($s_t = 1$), and in the other to high volatility ($s_t = 2$).

[75] Following Ang and Bekaert (2004), the SDMM is conditional on the smoothed probabilities of the high (low) market volatility state being lower (higher) than 50 per cent. More precisely, the expected return for each region is calculated as a product of estimated betas and world market expected returns, with smoothed probabilities of high (low) market volatility being lower (higher) than 50 per cent.

The modified linear MM specification with state dependency is applied by allowing the parameters to be time-varying to generate the expected returns.

$$r_t^i = \alpha_{s_t}^i + \beta_{s_t}^i r_t^w + \varepsilon_{s_t}^i \qquad \varepsilon_{s_t}^i \sim N(0, \sigma_{i,s_t}^2) \tag{5.7}$$

Where $\alpha_{s_t}^i$ denotes state-dependent alphas, $\beta_{s_t}^i$ denotes betas, and $\varepsilon_{s_t}^i$ is idiosyncratic volatilities for market excess returns based on the realization of the state probability (Appendix C for further explanation on filtered and smoothed probabilities).

When the state probability is realized, equation (5.7) can be defined as:

$$r_t^i = \alpha_1^i + \beta_1^i r_t^w + \varepsilon_1^i \tag{5.8}$$

When state probability $p_t > 0.5$, or

$$r_t^i = \alpha_2^i + \beta_2^i r_t^w + \varepsilon_2^i \tag{5. 9}$$

When state probability $p_t < 0.5$.

More precisely, we assume that $s_t = 1$ denotes a low variance state, and $s_t = 2$ denotes a high variance state. Then σ_{i,s_t}^2 is defined as the conditional variance[76] of residuals where $\sigma_{i,2}^2 > \sigma_{i,1}^2$.

5.4.3 Asset Allocation Strategy

This section explains the process underlying the asset allocation strategy based on implementing the SDMM for developed and emerging equity markets. To carry out the asset allocation strategy, the mean-variance optimization following Ang and Bekaert (2004) is applied.

To estimate the expected returns and variance-covariance matrices associated with each state, we define the vector of conditional expected returns for each region to depend on state i, $e_{s_{t=i}}$, where i implies the current state according to smoothed probabilities. We allow the variance-covariance associated with each state to be Σ_i. They will be specified in equations (5.13) and (5.14).

Because the world expected returns switch between two states, the expected returns for each region, given by $\alpha_i + \beta_i e_i^w$, vary across states. We have e_i^w defined in equations (5.3) and (5.5),

[76] We could either have a conditional mean or a conditional variance model.

with $\alpha_i$and β_i as vectors defined in equations (5.8) and (5.9) as the parameters of SDMM for the six regions. Therefore, the expected returns for each region are specified as:

$$e_{s_{t=i}} = \alpha_{s_{t=i}} + \beta_{s_{t=i}} e_i^w \qquad (5.\ 10)$$

Where the expected returns for each region vary depending on their different alphas and betas with respect to the realization of state probabilities for world market returns using smoothed probabilities.

The variance-covariance matrix has three elements. First, there is idiosyncratic volatility, σ_i, for each region that we obtain by matrix v_i for the state i:

$$v_i = \begin{bmatrix} (\bar{\sigma}_i)^2 & 0 \\ 0 & (\bar{\sigma}_i)^2 \end{bmatrix} \qquad (5.\ 11)$$

Where v_i is a matrix of zeros with $(\bar{\sigma}_i)^2$ along the diagonal. Second, the difference in systematic risk, β_i, through different regions and their correlations is given by the world market variance and the betas like a normal model:

$$\Omega_i = (\beta_i \beta_i')(\sigma_i^w)^2 + v_i \qquad (5.\ 12)$$

Since the variance of the world market and betas for the next period, time $t + 1$, relies on the realization of the current state, time t, we obtain two possible variance matrices for the expected returns next period.

Third, because the covariance matrix accounts for state structure, it is associated with the realization of the current state. As a result, the covariance matrix has an additional jump component to the conditional variance matrix, which again arises because the conditional means are different across two states. Therefore, the conditional covariance matrix associated with each state is defined as:

$$\Sigma_1 = p_{11}\Omega_1 + (1 - p_{11})\Omega_2 + p_{11}(1 - p_{11})(e_1 - e_2)(e_1 - e_2)' \qquad (5.\ 13)$$

$$\Sigma_2 = (1 - p_{22})\Omega_1 + p_{22}\Omega_2 + p_{22}(1 - p_{22})(e_1 - e_2)(e_1 - e_2)' \qquad (5.\ 14)$$

Where Σ_1 is the conditional covariance matrix if the current state is State 1 and Σ_2 is the conditional covariance matrix if the current state is State 2.

To perform mean-variance optimization, we need to specify the risk-free rate. In this regard, for each period, we assume the risk-free rate to be the weekly 3-month US T-bill rate; hence, the risk-free rate will vary over time.

The SDMM provides two optimal tangency portfolios (for all the equity regions) that investors can select, depending on the state realization. One obvious issue as indicated in the literature is that (1) mean-variance portfolios based on historical data may be quite unbalanced, and (2) rational investors do not apply straightforward portfolio weights (Black & Litterman, 1992; Green & Hollifield, 1992). One practical solution, therefore, is to impose a constraint on the asset allocation program as recommended by Ang and Bekaert (2004) for future studies. For instance, Dou et al. (2014) perform two alternative constraints on SDMM: The short-sale constraint requires the optimal portfolio weights to be positive, while the benchmark constraint keeps the asset allocation close to their average market capitalization (e.g., not more than 10 per cent deviation from market capitalization).

5.4.4 Performance Measurement

There are several measures which can be used to assess portfolio performance, where these measures differ depending on the type of risk measure under consideration. The most commonly used risk-return measure is the Sharpe ratio, which is ratio of the excess returns over the standard deviation (Sharpe, 1966). The Sharpe ratio is commonly used as a criterion for rational investors to develop an optimal strategy and decide between different possible investments. The Sharpe ratio refers to this measurement:

$$SR = \frac{(r_{i,t} - r_{f,t})}{\sigma(r_{i,t})} \tag{5. 15}$$

Where $r_{i,t}$ refers to the returns on portfolio i and $r_{f,t}$ denotes for the risk-free rate. This ratio gives the excess returns per unit of risk associated with the investment on a portfolio. In practice, a higher ratio implies better performance of the portfolio.

Two alternative measurements are Treynor's (1965) ratio and Jensen's (1968) alpha. However, as we adopted the mean-variance criterion to find the optimal portfolio weight, the Sharpe ratio is a more appropriate measure.

5.5 Empirical Results

Throughout this chapter the t statistic measures as the difference between the regression coefficients, $\hat{\alpha}$ and $\hat{\beta}$, and the hypothesised coefficients, α and β, divided by the standard error of the regression coefficients ($t = \frac{\hat{\beta}-\beta}{SE_{\hat{\beta}}}$). Using 1 per cent level of significance, the critical value of the t test would be 2.57, using 5 per cent level of significance the critical value would be 1.96, and using 10 per cent level of significance, the critical value would be 1.64.

Figures 4.3 and 4.4 plot the values of p_{11} and p_{22} given different values of $\Delta z_{m,t}$, the three-month interest rate and the five-year bond differential respectively.

Table 5.3 summarizes the results of the unconditional International MM estimated by OLS, and Newey-West and HAC standard errors were computed (Newey & West, 1987). The necessary condition for the model is that the intercept term *(α)* must be zero. Then we assume that the market is integrated with the world financial system if *β=1* and is segmented if *β=0*. First, the preliminary results for the unconditional International MM show that the $\hat{\alpha}$s are not significantly different from zero at conventional significance levels. Second, $\hat{\beta}$s in all of the markets are significant at 1 per cent level. The value of $\hat{\beta}$s for Emerging Europe (1.40), Europe (1.15) and Latin America (1.28) imply high volatility relative to the world market. However, the high systematic risk is due to the general increase in correlation observed during market turbulence and does not necessarily involved higher expected returns. We are more interested in checking whether the downside risk of emerging markets is as high as indicated by beta estimates.

Since historical data were used to estimate the market risk premium, and the sample contains episodes where large losses were incurred, it is likely that the model would generate poor estimates of expected returns. This is reasonable because the leverage effect, which is caused by negative shocks, stimulates volatility and hence expected returns.[77] In fact, the model is inadequate because time varying betas are not part of the model. There is a negative correlation between asset prices and changes in volatility; assets with lower prices than expected tend to

[77] The term "leverage effect" refers to one possible economic explanation for this phenomenon: a decrease in asset prices will cause the debt to equity ratio to increase, which makes the asset riskier and hence drives up volatility in asset prices for investors (Black, 1976; Christie, 1982). The reason for this is that when the asset price of a company that uses debt and equity finance drops, this will increase the debt to equity ratio, which in turn leads to higher volatility in asset prices. Higher volatility further drops asset price and increases leverage. In other words, other things being equal, bad news leads to higher leverage ratios, which in turn increases volatility. In fact, there is a negative correlation between asset prices and the changes in volatility: assets with lower prices than expected tend to have high volatility and assets with higher prices than expected tend to have low volatility.

have high volatility and assets with higher prices than expected tend to have low volatility. More specifically, high (low) returns and low (high) volatility states are associated with the existence of bull and bear markets (Ang & Bekaert, 2004; Dou et al., 2014; Liu, Margaritis, & Wang, 2012).

Table 5.3 Unconditional International MM-OLS parameters estimates

This Table reports the results of the unconditional International MM. Standard errors are in parentheses.

	Emerging Asia	Pacific	Emerging Europe	Europe	Emerging Latin America	North America
alpha	0.0008	-0.0001	0.0001	-0.0001	0.0005	0.0001
	(0.0008)	(0.0006)	(0.0011)	(0.0004)	(0.0008)	(0.0003)
beta	0.9885	0.8137	1.3999	1.1544	1.2789	0.9389
	(0.0319)	(0.0250)	(0.0439)	(0.0154)	(0.0344)	(0.0115)
Idiosyncratic volatility	0.0218	0.0171	0.0300	0.0105	0.0235	0.0079
AIC	-4.8105	-5.2992	-4.1711	-6.2676	-4.6588	-6.8412

5.5.1 Model Estimation and Results

Table 5.4 Panel A includes the estimation results for the mean-variance model for world equity markets given in equation (5.1). We consider the first state as a normal period, where world equity markets have a yield of 0.33 per cent (17.16 per cent per year) with 1.43 per cent (10.31 per cent per year) volatility. On the other hand, when the world markets are in state 2, the high volatility state, it is expected to yield a negative return of -0.45 per cent (-23.40 per cent per year) and higher volatility of 3.61 per cent (26.03 per cent per year).

The estimated transitional probabilities are $p_{11} = 0.96$ and $p_{22} = 0.93$, which implies that once the market is in state 1 today, it will remain in the same state the next period 96 per cent of the time. Accordingly, there is only a 4 per cent likelihood that the market will switch into a highly volatile state (state 2). Similarly, there is only a 7 per cent likelihood that it will switch out of the highly volatile state, meaning that each of these states is persistent. As Hamilton (1990) noted, we can use these transition probabilities to measure the approximate time duration in which the world market system stays in a given state by calculating the maximum number of corresponding periods, defined as $P(S_{t+n} = i, S_{t+n-1} = i, \dots, S_{t+1} = i|\, S_t = i) > 0.5$.

Table 5.4 SDMM parameter estimations (FTP)

Panel A reports the results for equations (5.1) and (5.2) where μ_1 and μ_2 are the conditional mean (expected returns) and $\sigma_1$and σ_2 are the conditional variances (volatility) for the world equity returns in states 1 and 2 respectively and $p_{11}$and p_{22} are transitional probabilities to stay in the same state and the expected duration for the world market returns. Panel B reports the parameters estimation for regional returns from equations (5.8) and (5.9). All the parameters are presented on a weekly basis. Standard errors are in parentheses.

A.	Estimates	μ_1	μ_2	σ_1	σ_2	p_{11}	p_{22}
		0.0033	-0.0045	0.0143	0.0361	0.9624	0.9306
		(0.0006)	(0.0022)	(0.0002)	(0.0006)		
	Expected duration					27	14
B.		Emerging Asia	Pacific	Emerging Europe	Europe	Latin America	North America
	State 1						
	Alpha	0.0013	0.0003	0.0007	-0.0001	-0.0001	0.0000
		(0.0008)	(0.0006)	(0.0011)	(0.0004)	(0.0008)	(0.0003)
	Beta	1.0986	0.9674	1.3347	1.1479	1.3834	0.8963
		(0.0566)	(0.0450)	(0.0777)	(0.0275)	(0.0581)	(0.0193)
	Idiosyncratic volatility	0.0166	0.0175	0.0140	0.0241	0.0085	0.0180
		0.0013	0.0003	0.0007	-0.0001	-0.0001	0.0000
	AIC	-5.2446	-5.7020	-4.6089	-6.6856	-5.1895	-7.3906
	State 2						
	Alpha	-0.0009	-0.0021	-0.0005	-0.0001	0.0009	0.0006
		(0.0017)	(0.0013)	(0.0024)	(0.0008)	(0.0019)	(0.0006)
	Beta	0.9490	0.7611	1.4128	1.1562	1.2541	0.9533
		(0.0467)	(0.0357)	(0.0648)	(0.0226)	(0.0523)	(0.0176)
	Idiosyncratic volatility	0.0277	0.0280	0.0214	0.0388	0.0135	0.0313
	AIC	-4.3062	-4.8415	-3.6529	-5.7625	-4.0822	-6.2590

It follows that the expected period of remaining in each state can be estimated as $\frac{1}{1-p_{11}}$, where p_{11} is the estimated transitional probability. The expected duration of being in each of these states are approximately 27 and 14 weeks respectively (Table 5.4, Panel A).

Table 5.4, Panel B, contains the estimation results for the SDMM: equations (5.8) and (5.9). First, the $\hat{\alpha}$s are not significant at the conventional level. Second, $\hat{\beta}$ estimates are significant at 1 per cent level in both states and are economically reasonable. $\hat{\beta}$s for the Emerging Europe, Europe and North American regions increase significantly in state 2, supporting the hypothesis that the equity markets are more correlated with each other during the bear market. These findings are in line with the results achieved by Ang and Bekaert (2002a) and Longin and Solnik

(2001), who indicate that international equity markets are more correlated with each other in bear markets than in bull markets. However, this is not the case for all the equity regions. For example, the Pacific region has a beta of 0.96 during the normal period but much lower systematic risk (0.76) in the bear market. In addition, it seems that the low beta for the Pacific region is offset by a large negative alpha in state 2, indicating that the assets in this region may be priced locally. In other words, the underperformance of the Pacific region during bear markets is much more related to idiosyncratic events since the Pacific region has the lowest average returns in the data (Dou et al., 2014).

Overall, we find strong evidence for state-dependent beta coefficients. These findings imply that the estimated beta from the unconditional International MM underestimates the risk premium during high volatility states while overestimating the risk premium during low volatility states. The SDMM allows the market risk premium to be drawn from two distinct states to characterize the instability of beta. The flexibility in the model enables portfolio managers to achieve more precise expected returns during different time periods that will give a reliable forecast of the portfolio performance.

Panel A of Table 5.5 shows the estimated expected returns computed using equation (5.10) with data from January 2001 to December 2015 for six equity regions. The expected excess returns may seem high during normal periods but negative during world market turbulence. However, they are conditional on the realization of bull and bear markets, and because betas are greater than 1 for Emerging Asia, Emerging Europe and Latin America, the expected excess returns are quite high in these regions. In the bear market, state 2, expected excess returns are significantly lower and negative, with the Pacific and Emerging Europe having the lowest expected excess returns. Since historical data are used, it is expected that high beta regions will have lower expected returns from the SDMM. The expected returns for Emerging Europe as estimated by the model are the highest of all the regions in the normal state but the lowest in the bear market.

Following the example of Ang and Bekaert (2004), Panel B of Table 5.5 reports the covariance and correlation matrix for each state obtained from equations (5.11) to (5.14). As expected, the average correlations are approximately 20 per cent higher in state 2 (0.55 in state 1 and 0.74 in state 2). In addition, the estimation procedure generates classification about the prevailing state in each period.

Table 5.5 SDMM estimation results (FTP)

The state-dependant excess returns, Panel A, are from equation (5.10) and the covariance of excess returns Panel B, are driven from estimates of equations (5.11) to (5.14). The correlations in Panel B are shaded. In Panel C, I computed the mean-variance efficient tangency portfolio weights by using an interest rate of 1.87 per cent, which is the average 3-month T-bill rate over the sample period. The MSCI average shows the average MSCI world index weight for each region across sample. All the numbers are annualized.

		Emerging Asia	Pacific	Emerging Europe	Europe	Latin America	North America
A.	State-dependant excess returns						
	State 1	0.2595	0.1850	0.2712	0.1954	0.2361	0.1567
	State 2	-0.2230	-0.2515	-0.2887	-0.2199	-0.1874	-0.1453
B.	State-dependent covariance and correlations						
	State 1						
	Emerging Asia	0.0307	0.6081	0.5556	0.5648	0.5720	0.4422
	Pacific	0.0161	0.0210	0.4511	0.5710	0.4551	0.4515
	Emerging Europe	0.0236	0.0164	0.0540	0.6069	0.6572	0.4153
	Europe	0.0146	0.0122	0.0209	0.0200	0.6556	0.6488
	Emerging Latin America	0.0209	0.0142	0.0319	0.0192	0.0404	0.5958
	North America	0.0091	0.0077	0.0119	0.0107	0.0137	0.0120
	State 2						
	Emerging Asia	0.0971	0.8209	0.7394	0.7238	0.7294	0.6432
	Pacific	0.0626	0.0605	0.7182	0.7413	0.6976	0.6438
	Emerging Europe	0.1034	0.0790	0.2029	0.7742	0.8283	0.6978
	Europe	0.0694	0.0560	0.1073	0.0952	0.7728	0.8541
	Emerging Latin America	0.0877	0.0660	0.1440	0.0921	0.1499	0.7550
	North America	0.0506	0.0399	0.0792	0.0665	0.0738	0.0641
C.	Tangency portfolio weight						
	MSCI average market cap	0.0732	0.1151	0.0073	0.2076	0.0140	0.5828
C1.	No constraints						
	State 1	0.3163	0.1096	0.0607	0.0929	-0.0749	0.4954
	State 2	-0.0670	-0.6780	0.0060	0.7799	0.0191	0.9400
	Unconditional	0.0400	-0.3058	0.1654	0.7310	0.1844	0.1849
C2.	Short-sale constraint						
	State 1	0.3059	0.1147	0.0380	0.0748	0.0000	0.4666
	State 2	0.0000	0.0000	0.0000	0.0000	0.0600	0.9400
	Unconditional	0.0000	0.0000	0.1220	0.5675	0.1507	0.1599

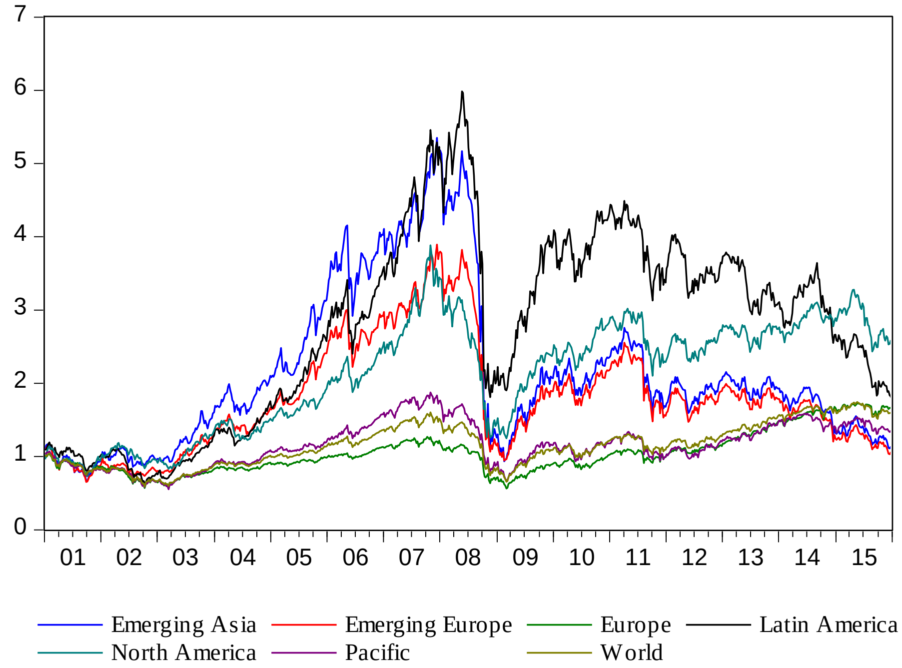
Panel C of Table 5.5 shows the tangency portfolios in state 1 and state 2 based on the returns, volatilities, and covariances/correlations matrices in Panels A and B. In the normal state 1, the model tells the investor to place 31 per cent of the portfolio wealth in Emerging Asian equity, which is quite different from the average relative market cap for the sample period. The Emerging European equity index is over-weighted relative to their market caps, but the European, Latin America and North American equity markets are underweighted (the allocation even calls for a short position in Latin American equity market in state 1. In state 2, the investor switches toward the less-volatile markets with better expected returns, which include the Europe and North American markets.

Looking at the emerging market index in Panel A of Figure 5.3, they historically outperformed developed markets. All the indices are set at $1 investment at early 2001. Although they were hit heavily by the GFC, the emerging market indices have shown steady growth.

Panel B of Figure 5.3 contains plots of the ex-ante (filtered) and ex-post (smoothed) state probabilities. The ex-ante probability is the probability that the state next week will be the low-volatility world market state, given past and current information up to time t; the ex-post probability is the probability that the state next time will be the low-volatility world market state, given all the information available in the sample period. This Figure points towards three periods during which the process was in the high variance state. These periods have quite intuitive interpretations in the context of this state-dependent model and do not necessarily reflect the business cycle. The first of these periods in 2001 was caused largely by the September 11 attacks and Dot-Com Bubble. There was also a market decline from late 2002 to early 2003, which corresponds to the Internet bubble bursting. The second period (2007–2010) is clearly driven by the GFC. The dotted lines show the two economic recessions, the 2001 Dot-Com Bubble and the GFC, also reported by the NBER. The third period (2011–2012) is a set of spikes of short duration, implying the European sovereign debt crisis. Overall, the unconditional probability of the normal state, bull market, is 66 per cent (Appendix A, equation (A.6)).

The results in Table 5.4 and 5.5, along with the plots in Figure 5.3, give a complementary description of the existence of two states for the world market, highlighting the fact that we need to account for the presence of at least two states when we look at portfolio performance and asset allocation strategy in financial markets.

A. Cumulated returns of $1 invested in the six regions January 2001–December 2015



B. Ex-ante and ex-post state probabilities of being in normal state (state 1)

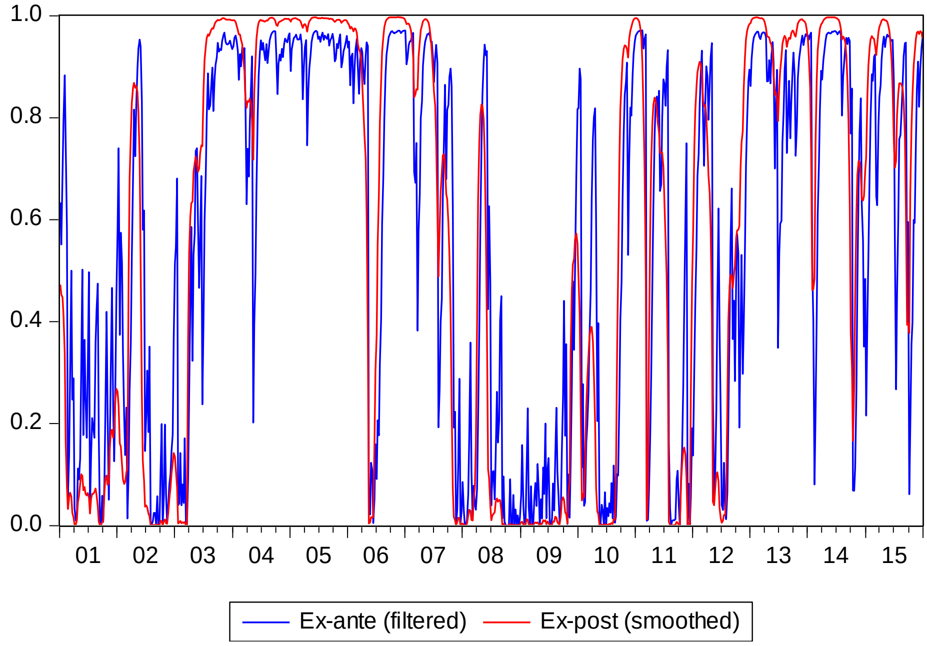


Figure 5.3 Cumulated historical returns and ex-ante and ex-post probabilities

Panel A shows the total returns of $1 invested in the six regions over the sample period. Panel B shows the ex-ante (filtered) and ex-post state probabilities. The ex-ante probability is the probability, given current information, and the ex-post probability is the probability, given all of the information present in data sample, that the state next week will be the world low-variance: the normal state.

5.5.2 State-dependent Asset Allocation Performance

Figure 5.3 illustrates the implementation of SDMM for asset allocation practice. The solid line shows the mean-standard deviation frontier when the unconditional International MM is used to estimate the expected returns. The other two frontiers are obtained from SDMM in the two states. The upper one in Figure 5.4 is for the normal state, state 1. The risk-return relationship is better in state 1 than the unconditional frontier. These results imply that the investor is now ascribing less likelihood to the bear market, high-volatility, for the next period.

In practice, the presence of two states and two tangency portfolios can provide state- dependent investment opportunities, which gives an advantage over a single unconditional tangency portfolio. More precisely, as indicated in Figure 5.3, the Sharpe ratio improved from 0.1586, using market capitalization weights, to 0.1718 using the optimal tangency portfolio. However, the optimal tangency portfolio remains almost at the same level as the market capitalization weighted portfolio when we use unconditional MVE. In state 2, the absolute value of Sharpe ratio is 0.36, which could marginally improve when holding the optimal tangency portfolio for the high-volatility state. In other words, investors can minimize losses on investments if they diversify their portfolio towards less volatile markets when the world market is in the high-variance state.

5.5.3 Can a State-dependent Asset-allocation Strategy be Improved by Allowing the Short-term Interest Rate to Determine the Market Phases?

So far, we have used world market returns[78] (an endogenous variable) to derive the volatility in equity returns, assuming either constant or fixed transition probabilities. One extension is to allow for TVTP, which requires an exogenous variable to influence the transition probabilities between the two market phases. In this case, we introduce an economic indicator, the short-term interest rate, to affect the transition probabilities. This model allows the short-term interest rate to show different behaviour during each market phase. Hence, a portfolio that trades based on state-dependent asset allocation with TVTP may offer additional returns values.

[78] World equity risk premium.

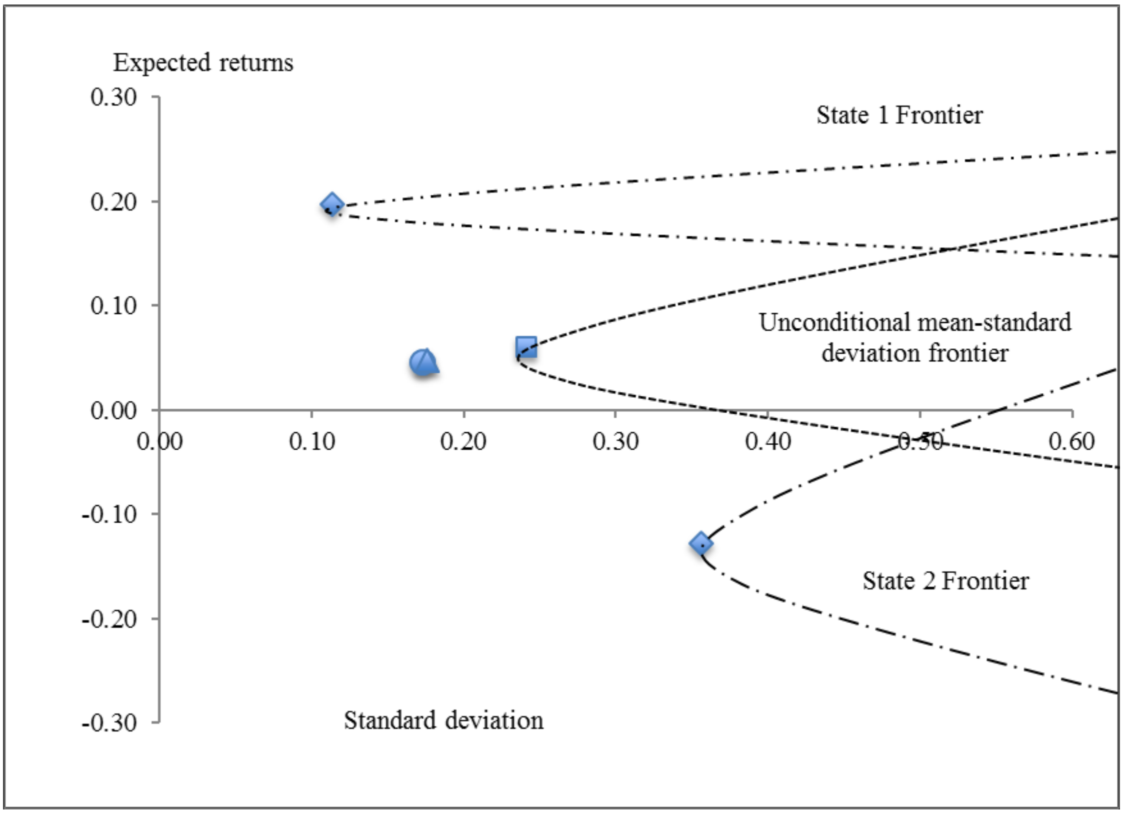


Figure 5.4 Mean-standard deviation frontier, 2001–2015

● World market portfolio (Sharpe ratio = 0.1611), ▲ Market capitalization (Sharpe ratio = 0.1586), ♦ MVE State 1 (Sharpe ratio = 1.71), ♦ MVE State 2 (Sharpe ratio = -0.36), ■ MVE Unconditional (Sharpe ratio = 0.1718). The expected returns are estimated from International MM defined in equation (3.3) and SDMM in equation (5.7) by using an average interest rate of 1.87 per cent. All the mean and standard deviation are annualized.

There is a long-held view in finance that a decrease in the level of the short-term interest rate is associated with an increase in equity prices (Fama & Schwert, 1977). Most previous studies have used the interest rate in conditional mean equations, thereby allowing only linear predictability (Reilly et al., 2007; Sweeney & Warga, 1986). On the other hand, studies such as (Chen, 2007) and Henry (2009) use interest rate risk both in mean equations and as a state predictor in Markov-switching frameworks.[79] However, Ang and Bekaert (2004) allow the interest rate to influence only the transition probabilities, so as a result the coefficients of expected returns were estimated with more precision.

As detailed in Section 4.3.2, in my study the transition probability matrix is allowed to vary depending on the changes in the level of the short-term interest rate, as follows:

[79] They find that monetary policy has different effects depending on market phases.

$$p_{ij}(z_{m,t}) = \begin{bmatrix} p_{11}(z_{m,t}) & 1 - p_{22}(z_{m,t}) \\ 1 - p_{11}(z_{m,t}) & p_{22}(z_{m,t}) \end{bmatrix} \quad (5.16)$$

Where $p_{ij}(z_{m,t}) = Pr\{s_t = j | s_{t-1} = i, z_{m,t}\}$ for $i, j = 1, 2$ and where the history of the economic-indicator variable is $z_{m,t} = \{i_{m,t}, i_{m,t-1}, \dots\}$. The interest rate differentials $\Delta z_{m,t} = i_{m,t} - i_{m,t-1}$ measure the slope of the yield curve for the US. In fact, $\Delta z_{m,t} = i_{m,t} - i_{m,t-1}$ (for $m =$ three-month interest rate) captures changes in the yield curve for different maturities. Thus p_{11} and p_{22} are now time-varying, which means that the probability of remaining in state 1 and state 2 may be different depending on whether the interest rate is high or low. In fact, the interest rate influences transitions between the states, and thus it indicates time variation in expected returns. In this specification, p_{11} and p_{22} are positive and are bounded between (0, 1) to well-characterized log-likelihood functions.

$$p_{11} = \frac{exp(\theta_1 + \theta_2 z_{m,t-1})}{1 + exp(\theta_1 + \theta_2 z_{m,t-1})} \text{ and } p_{22} = \frac{exp(\eta_1 + \eta_2 z_{m,t-1})}{1 + exp(\eta_1 + \eta_2 z_{m,t-1})} \quad (5.17)$$

Figure 5.5 shows the transition probabilities as a function of the interest rate differential. Note that p_{11} is the probability, given that the markets are currently in state1, of remaining in state 1. As interest rates increase, the probability of transitioning into the low-volatility market increases. In addition, p_{22} is the probability, given that the markets are in state 2, of staying in state 2. In the high-volatility state, as interest rates move lower, the probability of remaining in this state increases. Thus, the model in which p_{11} and p_{22} are fixed is strongly statistically rejected. Hence, nonlinear predictability is an important feature of the data. The TVTP parameters are also present in Table 5.6 Panel A. The long-term probability of the normal state indicated by the model is now 0.62.

It is also important to note that all the calculations from equation (5.3) to equation (5.14) remain unchanged. The estimation of conditional expected returns and standard deviations is like the procedure in Section 5.4, except that the transition probabilities vary over time depending on the level of interest rate.

Table 5.4 Panel A includes the estimation results for the mean-variance model for the world equity markets, equation (5.1). During normal periods the world equity markets have a yield of 0.33 per cent (17.16 per cent per year) with 1.39 per cent (10.02 per cent per year) volatility. It is also expected that the world markets to yield a negative return of -0.41 per cent (-21.32

per cent per year) and higher volatility of 3.57 per cent (25.74 per cent per year) during bad times.

The estimated transitional probabilities are $p_{11} = 0.96$ and $p_{22} = 0.92$ The expected durations of being in each of these states are approximately 26 and 13 weeks respectively (Table 5.4 Panel A). Table 5.4 Panel B contains the estimation results for the SDMM (TVTP), equations (5.8) and (5.9). The findings are quite similar to the previous section in that $\hat{\alpha}$s are not significant at the conventional level, whereas $\hat{\beta}$s are significant at 1 per cent level in both states and are economically reasonable.

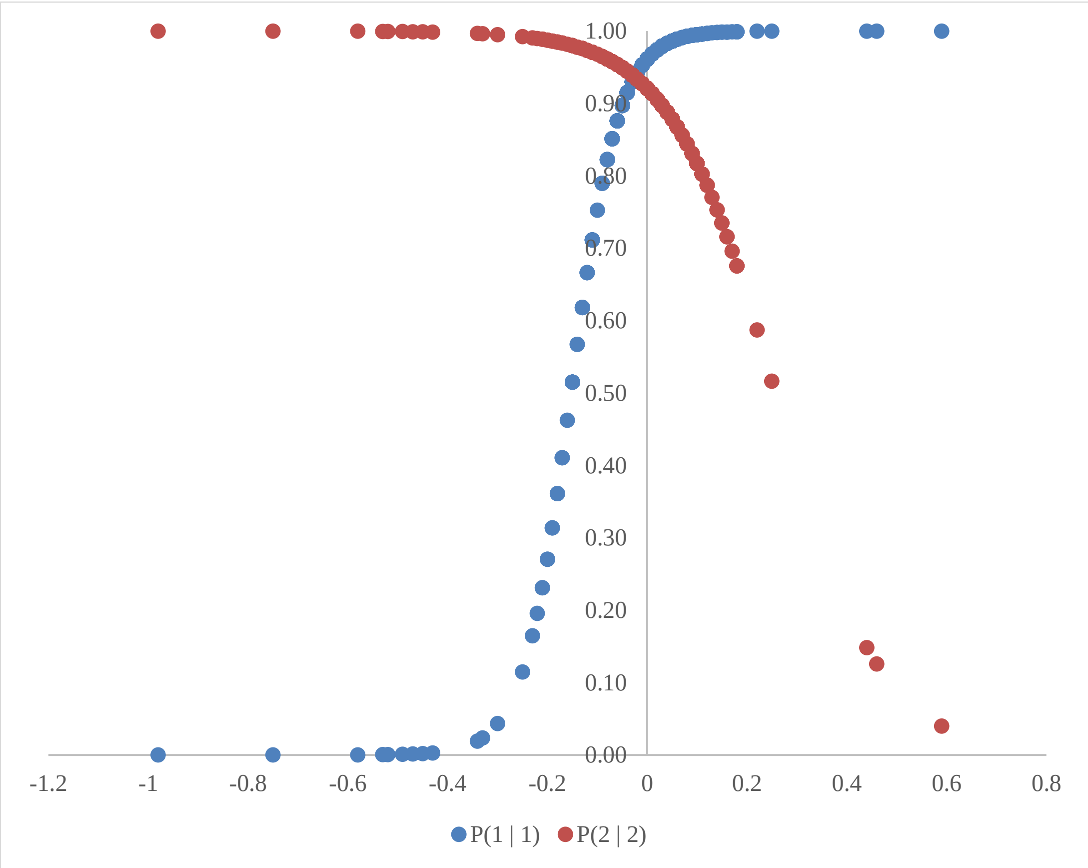


Figure 5.5 Time-varying transition probabilities of the market timing model and changes in the 3-month US T-bill rate

This Figure plots the values of p_{11} (blue dots) and p_{22} (red dots) given different values of $\Delta z_{m,t}$, three-month interest rate differential on horizontal axis.

Panel A of Table 5.7 shows the estimated expected returns computed using equation (5.10) with data from January 2001 to December 2015 for six equity regions. Panel B of Table 5.7 reports the covariance and correlation matrix for each state obtained from equations (5.11) to

(5.14). Panel C of Table 5.7 shows the tangency portfolios in state 1 and state 2 based on the returns, volatilities, and covariance/correlation matrices in Panels A and B.

Table 5.6 SDMM parameters estimations (TVTP)

Panel A reports the results for equations (5.1) and (5.16), time-varying transition probabilities, where μ_1 and μ_2 are the conditional mean (expected returns) and σ_1 and σ_2 are the conditional variances (volatility) for the world equity returns in states 1 and 2 respectively. p_{11} and p_{22} are the time-varying transitional probabilities for staying in the same state and the expected duration for the world market returns. Panel B reports the parameters estimation for regional returns from equations (5.8) and (5.9). All the parameters are presented on weekly basis. Standard errors are in parentheses.

A. Estimates	μ_1	μ_2	σ_1	σ_2	p_{11}	p_{22}
	0.0033	-0.0041	0.0139	0.0357	0.9615	0.9207
	(0.0006)	(0.0022)	(0.0002)	(0.0006)		
Expected duration					26	13
TVTP parameters	θ_1	θ_2	η_1	η_2		
	2.4523	-9.5496	-3.2174	-21.0485		
	(0.4202)	(3.8595)	(0.4102)	(10.2367)		

B.	Emerging Asia	Pacific	Emerging Europe	Europe	Emerging Latin America	North America
State 1						
Alpha	0.0001	0.0002	0.0003	-0.0002	-0.0004	0.0001
	(0.0008)	(0.0007)	(0.0011)	(0.0004)	(0.0008)	(0.0003)
Beta	1.0998	0.9786	1.3748	1.1693	1.4082	0.8817
	(0.0604)	(0.0477)	(0.0809)	(0.0289)	(0.0613)	(0.0204)
Idiosyncratic volatility	0.0179	0.0141	0.0239	0.0085	0.0181	0.0060
AIC	-5.2095	-5.6834	-4.6264	-6.6880	-5.1809	-7.3839
State 2						
Alpha	0.0013	-0.0018	0.0000	-0.0002	0.0011	0.0004
	(0.0016)	(0.0012)	(0.0023)	(0.0008)	(0.0018)	(0.0006)
Beta	0.9660	0.7654	1.4049	1.1508	1.2530	0.9537
	(0.0448)	(0.0344)	(0.0631)	(0.0218)	(0.0503)	(0.0169)
Idiosyncratic volatility	0.0272	0.0209	0.0384	0.0133	0.0306	0.0103
AIC	-4.3621	-4.8885	-3.6770	-5.7976	-4.1300	-6.3057

Table 5.7 SDMM estimation results (TVTP)

The state-dependant excess returns, Panel A, are from equation (5.10) and covariance of excess returns, Panel B, are driven from estimates of equations (5.11) to (5.14). The correlations in Panel B are shaded. In Panel C, I computed the mean-variance efficient tangency portfolio weights by using an interest rate of 1.87 per cent, which is the average 3-month T-bill rate over the sample period. The MSCI average shows the average MSCI world index weight for each region across sample. All numbers are annualized.

		Emerging Asia	Pacific	Emerging Europe	Europe	Emerging Latin America	North America
A.	State-dependant excess returns						
	State 1	0.1983	0.1830	0.2553	0.1959	0.2273	0.1624
	State 2	-0.0868	-0.2196	-0.2276	-0.1948	-0.1447	-0.1357
B.	State-dependent covariances and correlations						
	State 1						
	Emerging Asia	0.0336	0.6389	0.5125	0.5415	0.5155	0.3946
	Pacific	0.0187	0.0226	0.4567	0.5511	0.4363	0.4226
	Emerging Europe	0.0258	0.0192	0.0598	0.6056	0.6507	0.4096
	Europe	0.0165	0.0137	0.0243	0.0229	0.6503	0.6367
	Latin America	0.0224	0.0160	0.0362	0.0220	0.0447	0.5877
	North America	0.0102	0.0086	0.0144	0.0127	0.0159	0.0138
	State 2						
	Emerging Asia	0.0933	0.8066	0.7577	0.7342	0.7534	0.6599
	Pacific	0.0588	0.0576	0.7122	0.7468	0.7030	0.6512
	Emerging Europe	0.1004	0.0740	0.1914	0.7732	0.8286	0.6951
	Europe	0.0666	0.0532	0.1006	0.0893	0.7738	0.8535
	Latin America	0.0858	0.0627	0.1355	0.0866	0.1411	0.7559
	North America	0.0492	0.0381	0.0742	0.0625	0.0696	0.0605
C.	Tangency portfolio weight						
	MSCI average market cap	0.0732	0.1151	0.0073	0.2076	0.0140	0.5828
C1.	No constraints						
	State 1	0.0559	0.2560	0.0566	0.1067	-0.0408	0.5656
	State 2	0.8477	-0.2284	0.0056	0.0746	0.0194	0.2810
	Unconditional	0.0400	-0.3058	0.1654	0.7310	0.1844	0.1849
C2.	Short-sell constraint						
	State 1	0.0494	0.2598	0.0435	0.0974	0.0000	0.5500
	State 2	0.9614	0.0000	0.0000	0.0000	0.0300	0.0086
	Unconditional	0.0000	0.0000	0.1220	0.5675	0.1507	0.1599

5.5.4 Practical Implementation

To demonstrate whether the state-dependent asset allocation adds value to standard mean-variance optimization, we estimate the returns of these two strategies both in-sample and out-of-sample performance. The state-dependent model estimated up to time t, and the state-dependent weights were calculated from information available up to time t, the estimation date. The test started with $1 investment in January 2001 and covered the period up to December 2008 for the in-sample period, and January 2009 to December 2015 for the out-of-sample period. Portfolio weights were re-estimated every week, which is consistent with data frequency. The performance criterion is the ex post Sharpe ratio. Following Bulla et al. (2011) in this chapter we account for transaction costs. The transaction costs are set to 10 basis points (0.10 per cent) for each time the market switches to different state.

The state-dependent strategy required the risk-free rate and the realization of the state. For the risk-free rate, we used the weekly US T-bill. To derive the state, we assumed that the investor computes the state probability from current information. If the state probability was larger than 50 per cent for state 1, the investor classified the state as 1; otherwise, it was classified as 2. This calculation did not require any further data input, as explained by Ang and Bekaert (2004).

Panel A Table 5.8 reports the in-sample average returns, standard deviations and Sharpe ratio estimated by the static mean-variance, state-dependent strategies (both with FTP and TVTP) and the MSCI world index for all equity asset allocation with (a) no constraints and (b) a short-sale constraint. Over the in-sample period, the state-dependent strategies yield higher average returns and less volatility in comparison to both world market returns and the static strategy with no constraint and short-sale constraint scenarios. Although the Sharpe ratio has a negative sign for the world returns, static strategy and state-dependent strategies, it indicates a better portfolio performance when a state-dependent strategy with FTP is used. Additionally, the Sharpe ratio for the state-dependent strategy marginally improves when the short-sale constraint is imposed, possibly because short-sale constraint restricts weights to be positive.

It is important to note that the reason for negative Sharpe ratios is that all of the equity market regions experienced extreme negative returns during the GFC, and if we exclude this time from the sample it will result in positive Sharpe ratios. However, in real world investment, extreme negative returns would be an inescapable part of portfolio returns during the period.[80]

[80] In order to eliminate the effect of GFC the sample is divided into two parts, namely in-sample and out-of-sample (in the calculation of Sharpe ratios, Table 5.8 and wealth accumulation, Figure 5.6) since GFC dimmed the benefit of the state-dependent model. Importantly, if the values in Panel A and Panel B in Table 5.8 are aggregated then the results would not "contradict intuition". The approach is consistent with Dou, Gallagher, Schneider, and Walter (2014).

Over the out-of-sample period and with no constraints, the state-dependent strategy's average returns are 14.82 per cent and 13.63 per cent for FTP and TVTP respectively, which is higher than the average returns of the static portfolio (13.70 per cent) and the world market returns (10.78 per cent): see Panel B of Table 5.8. The state-dependent portfolio's Sharpe ratio increased compared to the world market portfolio and static strategy. The state-dependent strategies did well because during this sample period, all equity markets recorded better returns as the world markets passed the GFC. In fact, under both no constraint and short-sale constraint, the state-dependent strategy delivers higher Sharpe ratios in the out-of-sample period, compared to the world market returns and the static strategy.

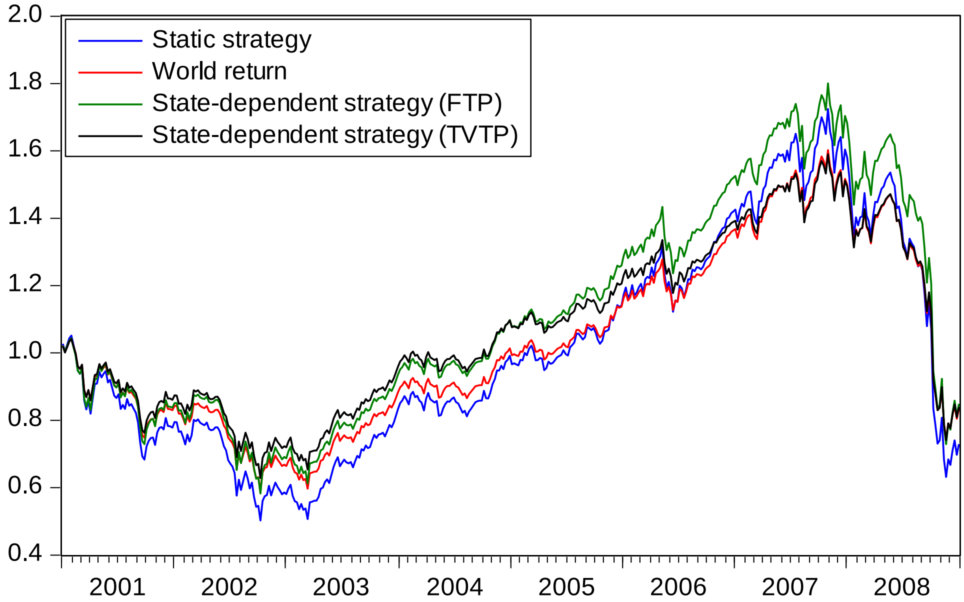
Table 5.8 In-sample and out-of-sample performance of all equity portfolios

The expected returns, standard deviation and the Sharpe ratio of both in-sample and out-of-sample returns based on static and state-dependent (after accounting for transaction costs) strategies. The Sharpe ratio is calculated from equation (5.15). All the returns and standard deviations are annualized, (i.e., ($r_i \times 52 \times 100$) and ($SD \times \sqrt{52} \times 100$)) and reported in percentages.

			No constraints			Short constraint		
		World	Static	SDMM (FTP)	SDMM (TVTP)	Static	SDMM (FTP)	SDMM (TVTP)
A.	In-sample performance 2001-2008							
	Mean returns (%)	-0.60	-0.80	0.93	0.1432	-0.77	2.77	0.31
	Standard deviation (%)	18.11	24.08	20.36	18.47	21.41	16.74	19.02
	Sharpe ratio	-0.14	-0.16	-0.11	-0.16	-0.18	-0.02	-0.15
B.	Out-of-sample performance 2009-2015							
	Mean returns (%)	10.78	13.70	14.82	13.63	12.27	13.09	13.17
	Standard deviation (%)	17.01	24.08	19.25	17.39	21.41	16.10	17.87
	Sharpe ratio	0.52	0.55	0.75	0.76	0.56	0.79	0.72

Figure 5.6 shows how wealth accumulated over time with different strategies before and after the GFC. Panel A shows that the state-dependent strategies performed relatively well but not very differently during the GFC. However, over the last five years the state-dependent strategies notably outperformed the static strategy. Given that the results in this example may be closely related to the historical period, the success of the state-dependent strategies presented here is not necessarily proof of future success. For instance, not all investors would choose a relatively large short position as imposed by the model.

A. In-sample wealth for various strategies, January 2001–December 2008



B. Out-of-sample wealth for various strategies, January 2009–December 2015

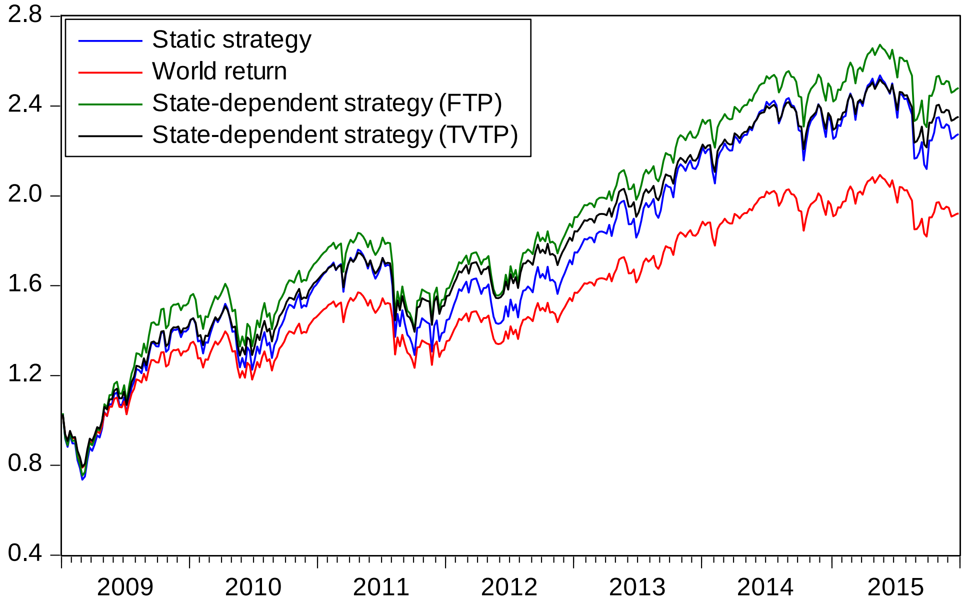


Figure 5.6 In-sample (Panel A) and out-of-sample (Panel B) wealth for all equity models

Panel A shows the in-sample wealth for the value of $1 invested from January 2001 to December 2008 for the state-dependent asset allocation strategies (after accounting for transaction costs) for the six regions with no constraint, compared with a static mean-variance strategy and the returns for the world markets. Panel B shows the out-of-sample wealth for the value of $1 invested from January 2009 to December 2015 for the state-dependent asset allocation strategies for the six regions with no constraint, compared with a static mean-variance strategy and the returns for the world markets.

5.6 Conclusions

The study presented in this chapter contributes to the body of research on asset allocation decisions and the portfolio selection process by providing a comparative analysis of the behaviour and performance of asset returns in both developed and emerging equity markets. It also contributes to the asset allocation literature by extending the state-dependent asset allocation strategy to emerging equity markets.

Using the MSCI country dataset for both developed and emerging equity regions, we show that emerging market regions exhibit time-varying correlation relative to the world capital markets and that market-timing can potentially enhance portfolio performance and provide diversification benefits. Overall, there is strong evidence for state-dependent beta coefficients. These findings show that the estimated beta from the unconditional International MM underestimates the risk premium required during high volatility states while overestimating the risk premium required during low volatility states. The SDMM allows the market risk premium to be drawn from two distinct states to characterize the instability of beta. These outcomes enable portfolio managers to more precisely forecast expected returns during different time periods and will give a more reliable measure of portfolio performance.

In addition, the empirical results suggest that the presence of two states and two tangency portfolios that account for the different distributions of asset returns is superior to a single unconditional tangency portfolio. More precisely, the Sharpe ratio improved from 0.55 to 0.75 by holding the optimal tangency portfolio with a state-dependent strategy in the out-of-sample portfolio. In other words, investors can optimize returns on their investments by using a state-dependent model when diversifying their portfolio towards emerging markets (i.e. Emerging Asia and Emerging Europe).

One important conclusion is that state-dependent strategies have the potential to outperform others because they set up a selective portfolio in a bear market that hedges against high correlations and low returns. This conclusion remains reliable in the presence of short-sale constraints because this portfolio inherently tilts the allocations toward the lowest-volatility assets. In addition, the state-dependent strategy need not be home biased; in this practical example, we involved internationally diversified portfolios by including emerging markets in the portfolio asset allocation. The analysis shows that diversification across emerging markets gives higher benefits to international investors.

The implementation of the state-dependent strategy can further be improved by incorporating the following extensions. First, expanding the asset classes: only equity markets are considered in this study, primarily to compare performance between equity markets in developed markets and in emerging markets. In contrast, Guidolin and Timmermann (2007), for example, use U.S. stocks, bonds and T-bills to test for the presence of state dependency in asset allocation decisions. Further research can look at the implications for performance of portfolios if bonds in both emerging and developed markets are included.

Second, in contrast to emerging markets, frontier markets can also offer significant diversification benefits (see, e.g., (Marshall, Nguyen, & Visaltanachoti, 2015)). Some studies show that frontier markets exhibit a different degree of co-movement with developed markets (Kiviaho, Nikkinen, Piljak, & Rothovius, 2014), with no indication of increasing integration through time (Berger, Pukthuanthong, & Yang, 2011). Further research can include frontier markets in portfolio optimization and the investment opportunities that these markets have to offer.

Finally, this chapter applies the SDMM model where beta is the only factor characterizing the expected returns. Another possible extension is to formulate expected returns from factor models such as a Fama and French three-factor model, or to incorporate other macroeconomic indicator variables, such as inflation, that can influence equity returns.

Chapter 6 Conclusion

6.1 Introduction

The objective of this thesis was to examine the use of various asset pricing models in asset allocation strategies within the emerging market settings. Given the significant growth and effect of the emerging markets on the global economy, this thesis provides researchers as well as practitioners with a specification that can better explain asset pricing behaviour in emerging markets. This research is useful as the asset pricing model incorporating time-varying risk premia and using a macroeconomic factor to identify the market phases provides new insight into asset return behavior in emerging markets.

The growth and development of international financial markets over the last three decades has made these markets more easily accessible and viable for international diversification and global investment, but optimal allocation of funds among international equity markets remains a challenging issue in portfolio management. While mean-variance portfolio optimization has been a widely accepted method used in international equity portfolio diversification, the time-varying nature of asset returns leads to non-normality in return distributions and makes identification of optimal portfolios problematic. Additionally, heterogeneity in time variation across financial markets causes time-varying correlations among international markets.

Asset pricing has been a central theme of finance research for over 50 years, with the CAPM providing a foundation for many of the developments in the area. A limitation of many asset pricing models is the failure to accommodate time variation in the market risk premium, which causes non-normality in the distribution of asset returns. As discussed in Chapter 1, a number of studies have found that time-varying volatility in the equity risk premium, and in betas, is associated with different market phases. The first empirical chapter of this thesis adopts Kim et al.'s (2004) approach to measuring time-varying volatility in the market risk premium and incorporates that into the study of the SD International CAPM.

While an endogenous variable such as the market risk premium can be used to identify market phases, finance research has also examined the use of exogeneous predictor variables to identify market phases. As discussed in Chapter 4, the predictive power of short-term interest rates for asset returns has a long history in finance (Fama & Schwert, 1977). Campbell and Ammer (1993) found that asset returns are driven by news about future excess returns, future inflation and the short-term interest rate. Other studies found that interest rate fluctuations are associated with equity price movements and may also cause changes in the volatility level of equity. The second empirical chapter of this thesis adopts Filardo's (1994) approach, assuming that the probability of switching is governed by US short-term and medium-term interest rates. We test the validity of the SD International CAPM by using an alternative method to model time-varying betas, and to evaluate whether the model can contribute to better explaining asset pricing returns.

A number of studies show that international markets are more correlated during periods of market recession than in normal times. Additionally, this changing correlation will impact on mean-variance portfolio optimization over periods of market downturns. The third empirical chapter of this thesis adopts the SD International CAPM developed in Chapters 3 and 4 to examine how these state-dependent models can be utilized in the context of country asset-allocation strategies. The more precise understanding of emerging market correlations offered by these models can potentially add value to portfolio performance and provide diversification benefits to international investors.

6.2 Thesis Summary

Chapter 2 gives an overview of the dynamics of emerging markets and the potential gains available to international investors from diversification in these markets. In doing so, the focus of this chapter is on the characteristics of emerging economies and the features that distinguish them from developed economies.

The world's equity market capitalization has experienced substantial growth and expansion and emerging economies have been the main sources of capital growth (Bekaert & Harvey, 2014). To a large extent, this rapid growth has been driven by the issuance of new shares and to a smaller extent by higher market returns (Blitz et al., 2013). There are two main reasons for equity investors to diversify their portfolio towards emerging economies. First, the correlation between developed and emerging markets, that may diminish the diversification benefit. However, studies find that the degree of correlation among these markets varies depending on market phases and that emerging markets offer increased diversification during market downturns (Christoffersen et al., 2012a). Second, though these markets are more influenced by political (Boutchkova et al., 2011; Chau et al., 2014), economic and exchange rate risks (Falcetti & Tudela, 2006), their higher expected returns make them attractive investment opportunities from the view point of international investors (Bekaert & Harvey, 1995; Bodie et al., 2013).

In this chapter we find that when we separate out the positive and negative returns, the downside risk of emerging markets is not as high as indicated by beta estimates. In fact, emerging markets perform similarly to developed markets in market downturns but outperform developed markets during normal times. This time-varying nature of returns indicates that emerging markets offer high returns but at higher risk. Given this evidence, investment flow to emerging markets can be further increased or decreased depending on which phase the market is in.

Chapter 3 tests whether expected returns in emerging economies can be explained by an SD International CAPM in which the market risk premium is used to identify the market phases. This chapter incorporates the global size and value risk factors to test whether these factors further explain expected returns. First, we find that some emerging markets demonstrate time-varying volatility depending on the world market phases. Second, the explanatory power of the SD International CAPM is better during financial recessions but is weak during expansionary phases. Third, although the explanatory power of the global risk factors of Fama and French is strong in a single state model, their power is limited when the conditional three-factor model with the state-dependent condition is used. This study finds that as markets with a lower degree of integration may be priced locally, investors can optimize their returns by investing in these markets. The practical implication of this finding is that investors considering diversifying their portfolios into emerging equity markets can provide some assurance in times of financial crisis. In this way the application of the state-dependent asset pricing model to emerging equity markets can be helpful for portfolio managers and practitioners.

Several studies have used monetary policy changes to explain equity price movements in domestic markets; however, there have been fewer studies focusing on the linkage between the changes in US monetary policy and international equity markets. Chapter 4 adopts an SD International CAPM to study the risk-return relationship in emerging markets. We use changes US monetary policy and changes in the market risk premium to identify the market phases. The method that is adopted in this study is a combination of two approaches: the International form of the CAPM and the state-dependent model with time-varying transition probabilities. This chapter considers two economic indicators, the US short-term interest rate and the five-year bond, as the key drivers of volatility in these regions, in addition to the market risk premium. While we find a marginal improvement in terms of model fitness compared to what was achieved in Chapter 3, the results suggest that most of these markets display evidence of two market phases associated with changes in the US interest rate level.

Allocation of funds among diverse financial markets is one of the most challenging issues for international investors and portfolio managers, especially in conditions such as the 2008 GFC. Although mean-variance portfolio optimization approaches are generally accepted, the time-varying nature of asset returns would lead to sub-optimal asset allocation decisions when we use historical data.

In Chapter 5, we implement a state-dependent Markov model to examine optimal portfolio decision among diverse financial markets; this model gives different distributions to asset returns, which in turn can extend the static mean-variance optimal model into dynamic portfolio optimization. Dynamic asset allocation enables investors and portfolio managers 1) to hedge against risk during bad times by investing in safer asset classes such as cash and bonds, and 2) to make optimal decisions during normal times by diversifying the portfolio into alternative asset classes. In this study, we implement a dynamic asset allocation and use emerging equity markets as an alternative asset class. We find that emerging markets expose time-varying correlation relative to world markets and this market-timing potentially adds value to portfolio performance and provides diversification benefits for international investors. Although these markets are classified as risky assets, their downside risks will be offset by their outperformance during normal times. Hence, investors can optimize the return on their investment by diversifying their portfolio towards emerging markets. The empirical outcomes of this study have practical implications for risk assessment of portfolios and asset allocation decisions across emerging markets.

6.3 Research Contributions

This thesis contributes to the body of knowledge about the performance of emerging markets during different market phases. It extends the analysis of the SD International CAPM with time-varying volatility behaviour to emerging markets and considers global factors as the key drivers of volatility in these regions.

Identification of market phases is a key component of the analysis. Market phases are identified in the first instance by the volatility in the market risk premium, and this is later augmented by exogeneous macroeconomic predictor variables, specifically the US short-term and medium-term interest rates, reflecting the pervasive effect in emerging markets of monetary policy changes in the US. The findings show that state dependent models outperform unconditional asset pricing models, including those augmented with size and value risk factors and GARCH models.

Better understanding of risk-return behaviour in emerging markets improves asset allocation decisions, leading to more efficient portfolio diversification. This thesis builds on current understandings of the asset allocation decision and portfolio management by adopting a developed model with time-varying volatility behaviour in global portfolio optimization. The empirical findings show that accounting for market phases identified by market risk premiums and monetary policy changes improves portfolio performance in global asset allocation settings.

6.4 Plan for Further Research

This thesis only considers risk and return behaviour in equity markets. Further research is planned that will examine its implications for the performance of bonds and other interest-rate-dependent securities in emerging markets using state-dependent asset pricing models. Additionally, these models may be more appropriate to some industries/sectors that are more affected by global news.

Additionally, this thesis applies the SD International CAPM model in which the world market risk premium and US monetary policy changes are the only factors characterizing the expected returns. Another possible extension is to incorporate local risk factors such as liquidity effects or momentum effects, or alternative macroeconomic variables such as inflation, GDP and government debt that can influence equity returns.

In contrast to emerging markets, frontier markets[81] can also offer significant diversification benefits. Current studies show that frontier markets exhibit a different degree of co-movement with developed markets, with no indication of increasing integration through time (Berger et al., 2011; Kiviaho et al., 2014). There is scope for further research to include frontier markets and the investment opportunities that these markets have to offer in portfolio optimization.

[81] The term frontier market is commonly used for equity markets that are smaller, illiquid and less accessible, but still investable, within developing countries. Frontier equity markets are commonly known by investors for having long-term return potential for investment as well as low correlations with other markets.

Exchange rate risk can also be an influential factor, depending on which currency is denominated. Throughout this thesis all equity returns are denominated in US dollars. Extending this analysis into alternative currencies (e.g., EURO) has the potential to offer further insights.

Ratner and Leal (1999) recommend adjusting returns for inflation when assessing emerging markets performance because some of these markets experienced high inflation (see also Alhashel, Almudhaf, and Hansz (2018)). These studies looked at the performance of emerging markets. However, noting that the aim of this thesis was not so much to assess the performance of EM but rather to examine whether the heterogeneity in time variation causes time-varying correlation among international markets, by using the SD International CAPM. And if that time-varying correlation can provide a reason for the failure of standard CAPM. returns.

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Appendix A Markov Chain with Transition Probability

Consider s_t as a random variable that could get the value of *1, 2… N*. The assumption is that the probability that s_t takes a particular value of j depends on the previous value s_{t-1} so that:

$$P\{s_t = j|s_{t-1} = i, s_{t-2} = 2, \dots\} = P\{s_t = j|s_{t-1} = i\} = p_{ij} \tag{A.1}$$

This process is a so-called N-state Markov chain with transition probability defined as $\mathrm{p_{ij}}$. Where the transition probability (p_{ij}) takes the probability that being in state j depends on state we (where $p_{i1} + p_{i2} + \cdots + p_{iN} = 1$) (Hamilton, 1994) .

Now consider the case of two states of a Markov chain in level, where $s_t = 1$ and $s_t = 2$ are defined as the unobserved states with low variance and high variance respectively and where the transition probability between the states is followed by a Markov chain of order one:

$$\begin{aligned} &P\{s_t = 1|s_{t-1} = 1\} = p_{11} \\ &P\{s_t = 1|s_{t-1} = 2\} = 1 - p_{11} \\ &P\{s_t = 2|s_{t-1} = 2\} = p_{22} \\ &P\{s_t = 2|s_{t-1} = 1\} = 1 - p_{22} \end{aligned} \tag{A.2}$$

It is sometime more suiTable to write the transition probability in the form of a matrix. Where in the case of two states, the transition probability takes the following form:

$$P\{s_t = j|s_{t-1} = i\} = \begin{bmatrix} p_{i1} \\ p_{i2} \end{bmatrix} = \begin{bmatrix} p_{11} & 1 - p_{22} \\ 1 - p_{11} & p_{22} \end{bmatrix} \tag{A.3}$$

Where : p_{ij}= *p(*S_t*=j* ∣ S_{t-1}*=i)*

The solution to find the unconditional probability of each state is to $|\mathrm{P} - \lambda \mathrm{I_N}| = 0$ (Where $\mathrm{I_N}$ is 2×2 identity matrix in the case of two states). Following the process given by Hamilton (1994), the unconditional probability that the process is in state 1 at any given time is:

$$\mathrm{P}\{\mathrm{s_t} = 1\} = \frac{1 - \mathrm{p_{22}}}{2 - \mathrm{p_{11}} - \mathrm{p_{22}}} \tag{A.4}$$

Similarly we could obtain the same value for state 2:

$$\mathrm{P}\{\mathrm{s_t} = 2\} = \frac{1 - \mathrm{p_{11}}}{2 - \mathrm{p_{11}} - \mathrm{p_{22}}} \tag{A.5}$$

To estimate the expected duration of being in each state, the occupation time is calculated as follows:

$$\sum_{k=1}^{T} k\, p_{11}{}^{k-1}(1 - p_{11}) = (1 - p_{11})^{-1} \tag{A.6}$$

$$\sum_{k=1}^{T} k\, p_{22}{}^{k-1}(1 - p_{22}) = (1 - p_{22})^{-1} \tag{A.7}$$

The significance of this application is that the occupation time of a typical event can be calculated from the estimation of maximum likelihood parameters and then a comparison with the historical average duration of the event (Hamilton, 1989).

Appendix B Expectation Maximisation Algorithm

In conducting SD International CAPM in this study, the parameters estimation is carried out by adopting the expectation maximisation (EM) algorithm of Hamilton (1990). The estimation procedure is outlined below:

The purpose is to perform a model with two states as the outcome of an unobserved two-state Markov chain where s_t is independent from ε_t (residuals) in both subsamples. Now consider $r_{i,t}$ as observed variable.

If the process follows by state $s_t = j$ at time t then the conditional density of r_{it} will take the form of:

$$f(r_{it} \mid s_t = j,\ r_{mt}\,; \theta) \tag{B. 1}$$

Where θ is defined as a set of parameters ($\theta \equiv \alpha_1\,, \alpha_2\,, \beta_1, \beta_2, \sigma_1^2\,, \sigma_2^2$)' determining the conditional density. If the process is in state 1, the observed variable r_{it} is drawn from a $N(\mu_1, \sigma_1^2)$ distribution. Alternatively, if the process is in state 2 then r_{it} has been drawn from a $N(\mu_2, \sigma_2^2)$ distribution. Therefore, the density of r_{it} conditional on the random variable $s_t = j$ is equation (B.1).

In this case θ consists of $\alpha_1\,, \alpha_2\,, \beta_1, \beta_2, \sigma_1^2$ and σ_2^2 and the two densities' functions considering *N=2* are:

$$\eta_t = \begin{bmatrix} f\ (r_{it} \mid s_t = 1,\ r_{mt}\ ; \theta) \\ f\ (r_{it} \mid s_t = 2,\ r_{mt}\ ; \theta) \end{bmatrix} = \begin{bmatrix} \dfrac{1}{\sqrt{2\pi\sigma_1^2}} exp\left\{\dfrac{-(r_{it} - \alpha_1 - \beta_1\, r_{mt})^2}{2\sigma_1^2}\right\} \\ \dfrac{1}{\sqrt{2\pi\sigma_2^2}} exp\{\dfrac{-(r_{it} - \alpha_2 - \beta_1\, r_{mt})^2}{2\sigma_2^2}\} \end{bmatrix} \tag{B. 2}$$

We assume that the conditional density, function (B.2), relies only on the previous state (smoothed probability).

Then the log likelihood function can be defined by getting the log of equation (B.1):

$$log\{f(r_{it} \mid s_t = j,\ r_{mt}\,; \theta)\} = log\ f\ (r_{i1}; \theta) + \sum_{t=2}^{T} log\ f\ (r_{it} \mid r_{mt}\,;\ \theta) \tag{B. 3}$$

That is given the numerical[82] ability to equation (B.1) to estimate the log likelihood function regarding the unknown parameters (α_1 ,α_2 , β_1, β_2 , σ_1^2 , σ_2^2) (Hamilton 1994, p. 133).

We assume that the conditional density function relies only on the previous state (smoothing probability). Then the log likelihood function can be defined by getting the log of equation (B.3). That is given the numerical ability of the equation (B.3) to estimate the log likelihood function regarding to the unknown parameters (α_1 ,α_2 , β_1, β_2 , σ_1^2 , σ_2^2) (Hamilton 1994, p. 133). This estimation procedure is explained in the following section.

[82] In addition to unknown parameters, this model involves an unobserved latent variable (Markov model). Therefore, an expected-maximization algorithm will be performed.

Appendix C Filtered and Smoothed Probabilities

Following Hamilton (1994), we can derive the unconditional probability that the process will be in state 1 at any given time is:

$$p(s_t = 1) = \frac{1-q}{(1-p)+(1-q)} \tag{C. 1}$$

The unconditional probability that the process will be in state 2 would be 1 minus p.Now the joint distribution of the two probabilities is:

$$\begin{aligned} p(s_t, s_{t-1}|Y_{t-1}; X_t) &= p(s_t|s_{t-1}, Y_{t-1}; X_{t-1}) \times p(s_{t-1}|Y_{t-1}; X_{t-1}) \\ &= p(s_t|s_{t-1}) \times p(s_{t-1}|Y_{t-1}; X_{t-1}) \end{aligned} \tag{C. 2}$$

The first line in equation (C.2) is given by the Bayes Theorem and the second is given by the independent principle of Markov chain. The transition probability $p(s_t|s_{t-1})$ and the filter probability $p(s_{t-1}|Y_{t-1}; X_{t-1})$, are known at time t, we can compute $p(s_t, s_{t-1}|Y_{t-1}; X_t)$.Summarizing s_{t-1} from equation (C.2), we get the conditional probability of s_t.

$$p(s_t|Y_{t-1}; X_t) = \sum_{s_{t-1}}^{2} p(s_t, s_{t-1}|Y_{t-1}; X_t) \tag{C. 3}$$

The joint distribution of y_t and s_t at time t can be computed:

$$p(y_t,\ s_t|Y_{t-1}; X_t) = f\ (y_t|\ s_t, Y_{t-1}; X_t)p(s_t|Y_{t-1}; X_t) \tag{C. 4}$$

The first part on the right-hand side of equation (C.4) is the likelihood function and the second part is from equation (C.3), so that equation (C.4) can also computed. As a result, the filter probability, the prevailing state at each point in time, is given by:

$$p(s_t|Y_t; X_t) = \frac{p(y_t,\ s_t|Y_{t-1}; X_t)}{p(y_t|Y_{t-1}; X_t)} = \frac{f(y_t|\ s_t, Y_{t-1}; X_t)p(s_t|Y_{t-1}; X_t)}{\sum_{s_{t-1}}^{2} f(y_t|\ s_t, Y_{t-1}; X_t)p(s_t|Y_{t-1}; X_t)} \tag{C. 5}$$

The filter probability, ex-ante, is the probability given past and current information up to time t. Alternatively, we can use all the information available in the sample period, ex-post, to derive the historical state that the process was in at time t. It is therefore more intuitive to employ all of the information available up to time T rather than t.Similarly, the smoothed probability, given all the information available up to time T, is as follows:

$$p(s_t|Y_T; X_T) = \sum_{s_{T-1}}^{2} p(s_T, s_t|Y_T; X_T) \qquad t = 1,2, \dots, T \tag{C. 6}$$

Appendix D The Log-linear Present Value Framework

Campbell and Shiller (1988) use a first-order Tylor series approximation to drive log-linear present value relationship for the fundamental component of stock price:

$$p_t = \frac{k}{1-\rho} + E\left[\sum_{j=0}^{\infty} \rho^j \left[(1-\rho)d_{t+1+j} - r_{t+1+j}\right] | I_t|\right] \tag{D.1}$$

p_t is the log price (ex-dividend) of stock at the end of time t, d_{t+1+j} is the log dividend at time $t+1+j$ claimed at the beginning of the period, r_{t+1+j} is log return on a stock or a portfolio held from $t+1$ to $t+1+j$, $E[.]$ The expectation operator, I_t is conditioning information set available at time t, and ρ and k are linearization parameters defined by $\rho \equiv 1/(1+\exp(\overline{d-p}))$, where $(\overline{d-p})$ is the average log dividend-price ratio and $k \equiv -\log(\rho) - (1-\rho)\log\left(\left(\frac{1}{\rho}\right) - 1\right)$. Empirically, for US data the average dividend price ratio has been about 4 per cent per annum, indicating $\rho \cong 0.997$ for monthly data (Campbell & Shiller, 1988).

Kim et al. (2004) develop a partial equilibrium model of volatility feedback based on equation (above) and two assumptions. First, they assume that news about future dividends is subject to a two-state Markov switching variance as follows:

$$\varepsilon_{m,t} \sim N(0, \sigma^2_{m,S_{m,t}}) \tag{D.2}$$

$$\sigma^2_{m,S_{m,t}} = \sigma^2_{m,0}\left(1 - S_{m,t}\right) + \sigma^2_{m,1} S_{m,t} \qquad \sigma^2_{m,0} < \sigma^2_{m,1}$$

$$Pr\{s_t = 0 | s_{t-1} = 0\} = p_m \text{ and } Pr\{s_t = 1 | s_{t-1} = 1\} = q_m$$

Where $\varepsilon_{m,t}$ stands for new information about future dividends that arrives during trading period t, $\sigma^2_{m,S_{m,t}}$ is the variance of $\varepsilon_{m,t}$, $S_{m,t}$ is a Markov-switching state variable that takes on structural values of 0 and 1 according to the prevailing volatility state, and p_m and $q_m$are the transition probabilities governing the evolution of S_t. Second, they assume that the expected returns for a given period $t+j$ are a linear function of market expectations about the volatility of news. Based on these assumptions and the Markov-switching specification for volatility, the expected return can be defined as a linear function of the conditional probability of the high volatility state.

$$E[r_{m,t+j} | I_{m,t}] = \mu_{m,0} + \mu_{m,1}\Pr[S_{m,t+J} = 1 | I_{m,t}] \tag{D.3}$$

Where $\mu_{m,0}$ is the expected return in an expected low variance state and $\mu_{m,1}$ presents the marginal effect on the expected return of an expected high variance state.

Now the log-linear present value model in equation (D.1) can be rearranged to show that realized return is determined by the expected return, volatility feedback and news (revision in expected return and revision in future dividends):

$$r_{m,t} = E[r_{m,t}|I_{m,t-1}] + f_{m,t} + \varepsilon_{m,t} \tag{D.4}$$

Where $f_{m,t}$ is volatility feedback term that shows revisions in future expected returns:

$$f_{m,t} \equiv -\{E[\sum_{j=1}^{\infty} \rho^j r_{t+j}\, |I_t^{'}] - E[\sum_{j=1}^{\infty} \rho^j r_{t+j}\, |I_{t-1}]\}$$

And $\varepsilon_{m,t}$ shows news about dividends:

$$\varepsilon_{m,t} \equiv E[\sum_{j=1}^{\infty} \rho^j \Delta d_{t+j}\, |I_t^{'}] - E[\sum_{j=1}^{\infty} \rho^j \Delta d_{t+j}\, |I_{t-1}]$$

Where revisions are made with additional information during period t which is collected in the information set I_t. $\varepsilon_{m,t}$ is news information about future dividends that arrives during period t (as in equation (D.1)). The information set $I_t^{'}$ includes all the components of I_t except the final realized value of r_t. It is vital to differentiate between $I_t^{'}$ and $I_t = \{I_t^{'}, r_t\}$ if equation (D.4) is to explain a meaningful causal relationship between dividend news $\varepsilon_{m,t}$ and volatility feedback $f_{m,t}$ to the final realized return r_t. Mayfield (2004) assume that investors know the previous volatility state with certainty, which is $I_{t-1} = \{S_{t-1}\}$, and investors face the possibility of a change in the volatility state by the end each point in time, which is $I_t = \{S_t\}$. In terms of Markov-switching volatility feedback model, Kim et al. (2004) use the assumption given in equations (D.2) and (D.3) to find empirically traceable expressions for the expected returns and news term in equation (D.4).

It is also useful to note that the expected return in equation (D.3) can be written as:

$$E[r_{m,t+J}|I_{m,t}] = \mu_{m,0} + \mu_{m,1}\Pr[S_{m,t} = 1] + \mu_{m,1}\lambda^J Pr(S_{m,t} = 1|S_t or\ I_t^{'}) - \Pr(S_{m,t} = 1)$$

where $\lambda \equiv p_m + q_m - 1 > 0$ following Hamilton (1989) and given recurring volatility states (i.e., $|\lambda| < 1$). Then the discounted sum of future expected returns is:

$$\mathrm{E}[\sum_{j=1}^{\infty} \rho^j r_{t+j}\, |I_t] = \frac{\mu_{m,0}}{1-\rho} + \frac{\mu_{m,1}}{1-\rho}\Pr[S_{m,t} = 1] + \frac{\mu_{m,1}}{1-\rho\lambda}(\Pr[S_{m,t} = 1|I_t] - Pr[S_{m,t} = 1]) \tag{D.5}$$

According to the equation (d.5) the volatility feedback term is:

$$f_{m,t} = -\frac{\mu_{m,1}}{1-\rho\lambda}\{Pr(S_{m,t} = 1|I_t^{\prime}) - \Pr[S_{m,t} = 1|I_{m,t-1}]\} \tag{D.6}$$

Therefore, replacing the empirically traceable expression as defined in equation (D.4), the Markov-switching model or equity premium with volatility feedback is:

$$r_{m,t} = \mu_{m,0} + \mu_{m,1}\Pr[S_{m,t} = 1|S_{m,t-1}] + \delta\{Pr[S_{m,t} = 1|S_{m,t}] - \Pr[S_{m,t} = 1|S_{m,t-1}]\} + \varepsilon_{m,t} \quad \text{(D. 7)}$$

Where $\varepsilon_{m,t} \sim N(0, \sigma^2_{m,S_{m,t}})$ is Markov-switching as described in equation (D.2) and the volatility feedback coefficient $\delta = \frac{-\mu_{m,1}}{1-\rho\lambda}$ as indicated by equation (D.6). To interpret the volatility feedback coefficient $= \frac{-\mu_{m,1}}{1-\rho\lambda}$, note that the parameter of linearization, ρ, which is the average ratio of the stock price to sum of the stock price and the dividend should be slightly be less than 1 in practice. For example, Campbell and Shiller (1988) estimated the value of $\rho \simeq 0.997$ for the US data where the average dividend price ratio has been about 4% per annum. Thus, a positive price of risk indicates that, if volatility states are persistent (i.e., $\lambda = p_m + q_m - 1 > 0$), the coefficient δ on the volatility feedback term will be negative. Conversely, any evidence of a negative volatility feedback effect indicates a positive relationship between market volatility and equity premiums (Kim et al., 2004). Kim et al. (2004) test the estimate of δ, with restriction, where $\rho = 0.997$ and $\lambda = p_m + q_m - 1$ to see if there is still a positive relationship between US stock market volatility and the equity premium. However, the main objective of this chapter is to use these estimates to test the efficiency of International CAPM. In addition, we use world market data in which the average dividend price ratio may vary from market to market.

Appendix E Variable Definitions

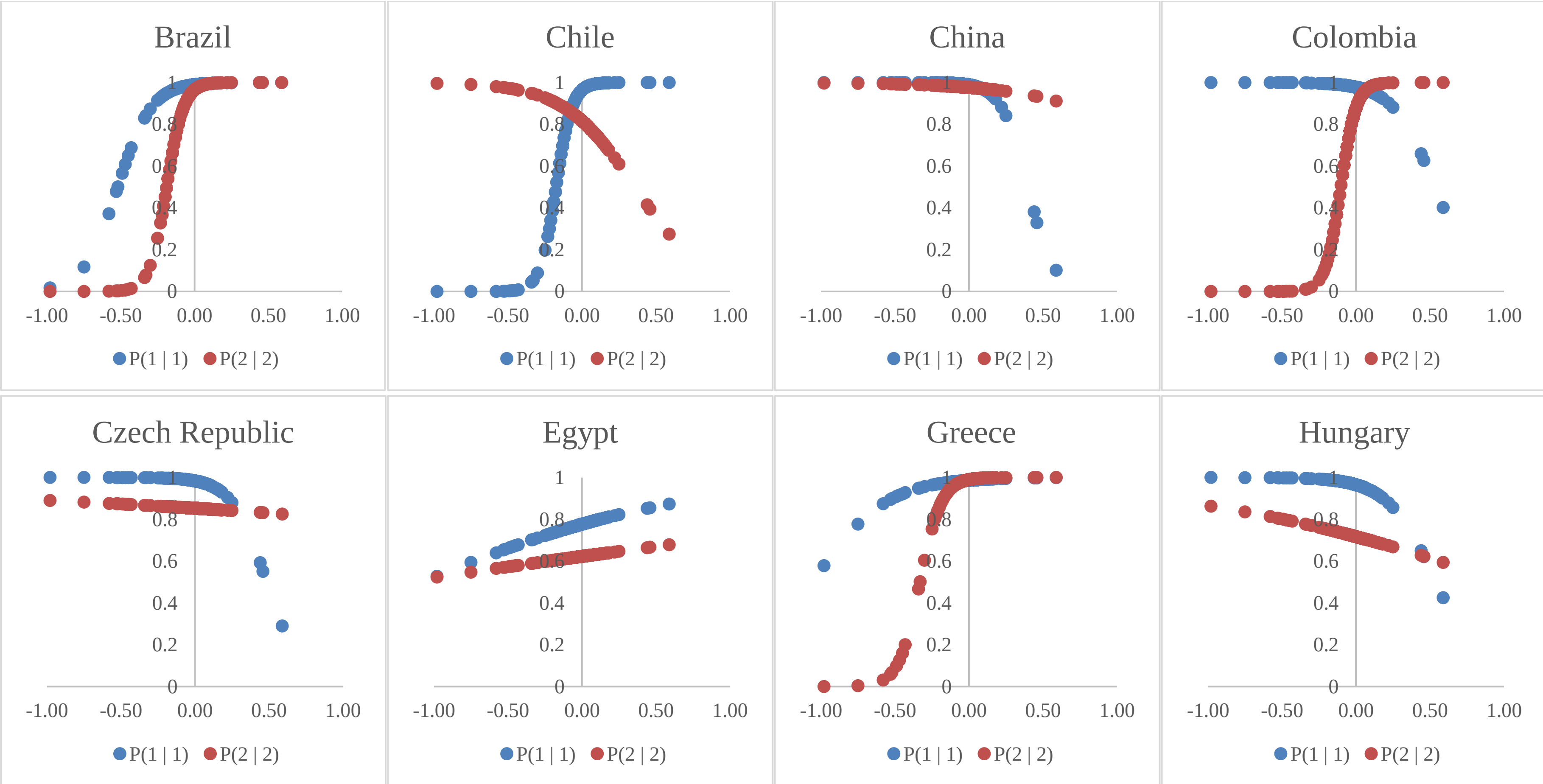
Table E1. Variable definitions

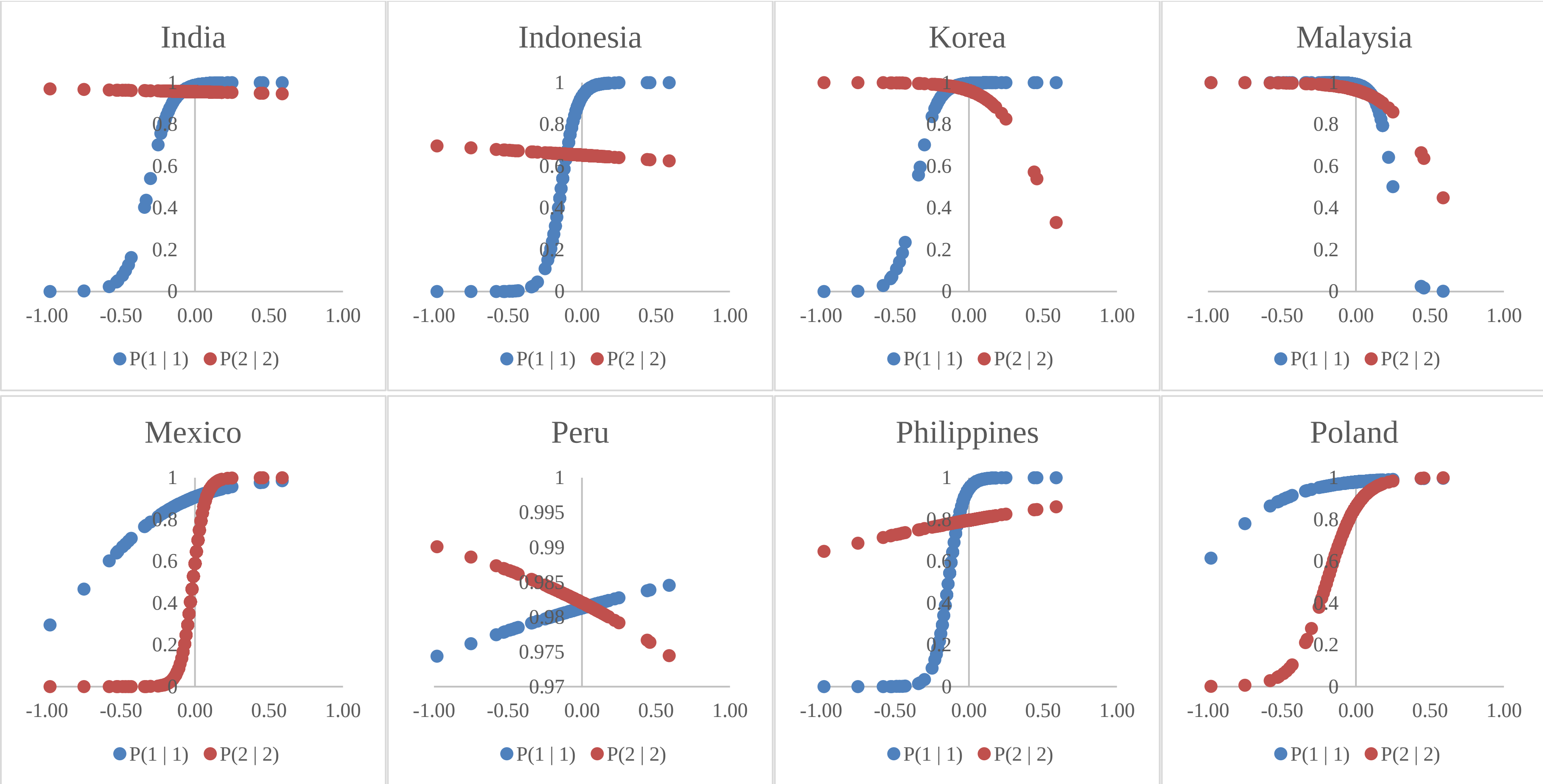
Indicator Name	Short definition
Population (Total)	Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship – except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. The values shown are midyear estimates.
GDP (Current USD)	GDP at purchaser's prices is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars.
Exports of goods and services (% of GDP)	Exports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments.
Inflation, consumer prices (%)	Inflation as measured by the consumer price index reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services that may be fixed or changed at specified intervals, such as yearly. The Laspeyres formula is generally used.
Stock market capitalization to GDP (%)	Total value of all listed shares in a stock market as a percentage of GDP.
Stock market total value traded to GDP (%)	Total value of all traded shares in a stock market exchange as a percentage of GDP.
Stock market turnover ratio (%)	Total value of shares traded during the period divided by the average market capitalization for the period.

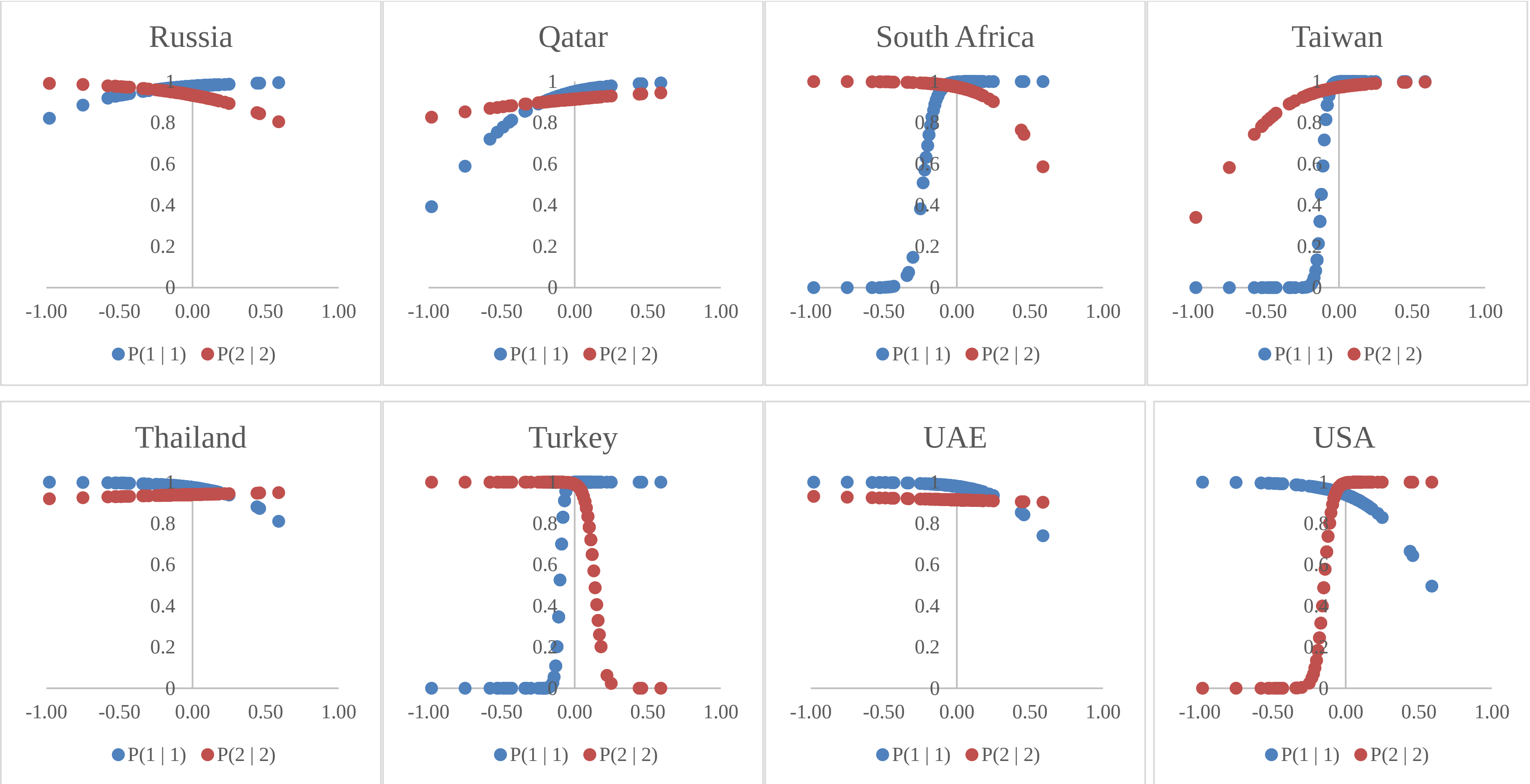
Table E2. Interest rate variable descriptions

Items	Description
Short-term rate	Treasury bills are short-term securities issued by the U.S. Treasury. Treasury Bills are traded in primary and secondary markets. Secondary trading in Treasuries occurs in the over-the-counter (OTC) market. In the secondary market, the most recently auctioned Treasury issue is considered current or on-the-run. Issues auctioned before current issues are typically referred to as off-the-run securities. In general, current issues are much more actively traded and have much more liquidity than off-the-run securities. This often results in off-the-run securities trading at a higher yield than similar maturity current issues. Rates are annualized using a 360-day year or bank interest on a discount basis.
5-year bond	Yields on Treasury nominal securities at "constant maturity" are interpolated by the U.S. Treasury from the weekly yield curve for non-inflation-indexed Treasury securities. This curve, which relates the yield on a security to its time to maturity, is based on the closing market bid yields on actively traded Treasury securities in the over-the-counter market. These market yields are calculated from composites of quotations obtained by the Federal Reserve Bank of New York.

Appendix F Time-varying Probabilities in Emerging Equity Markets and Changes in 3-month US T-bill Rate

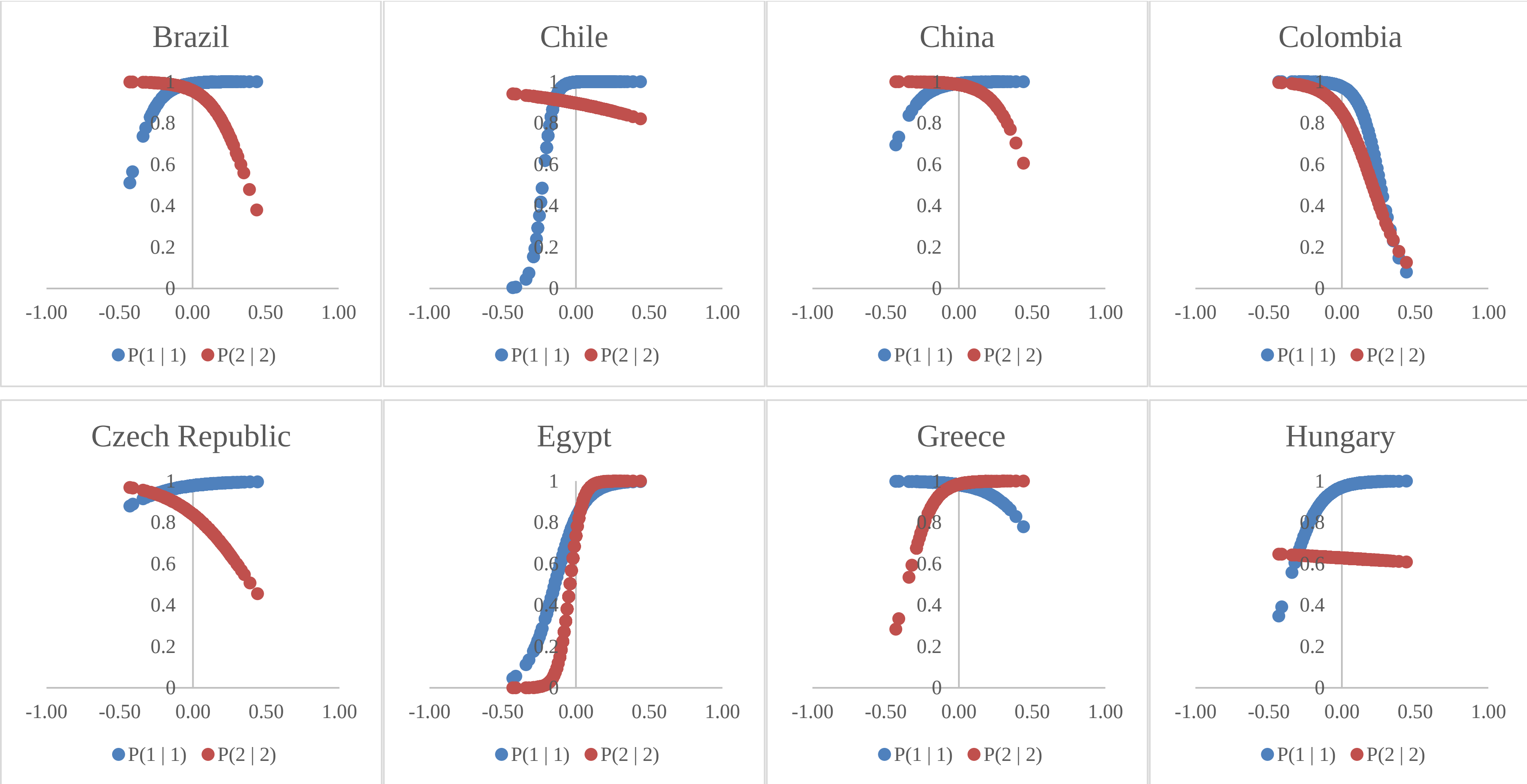


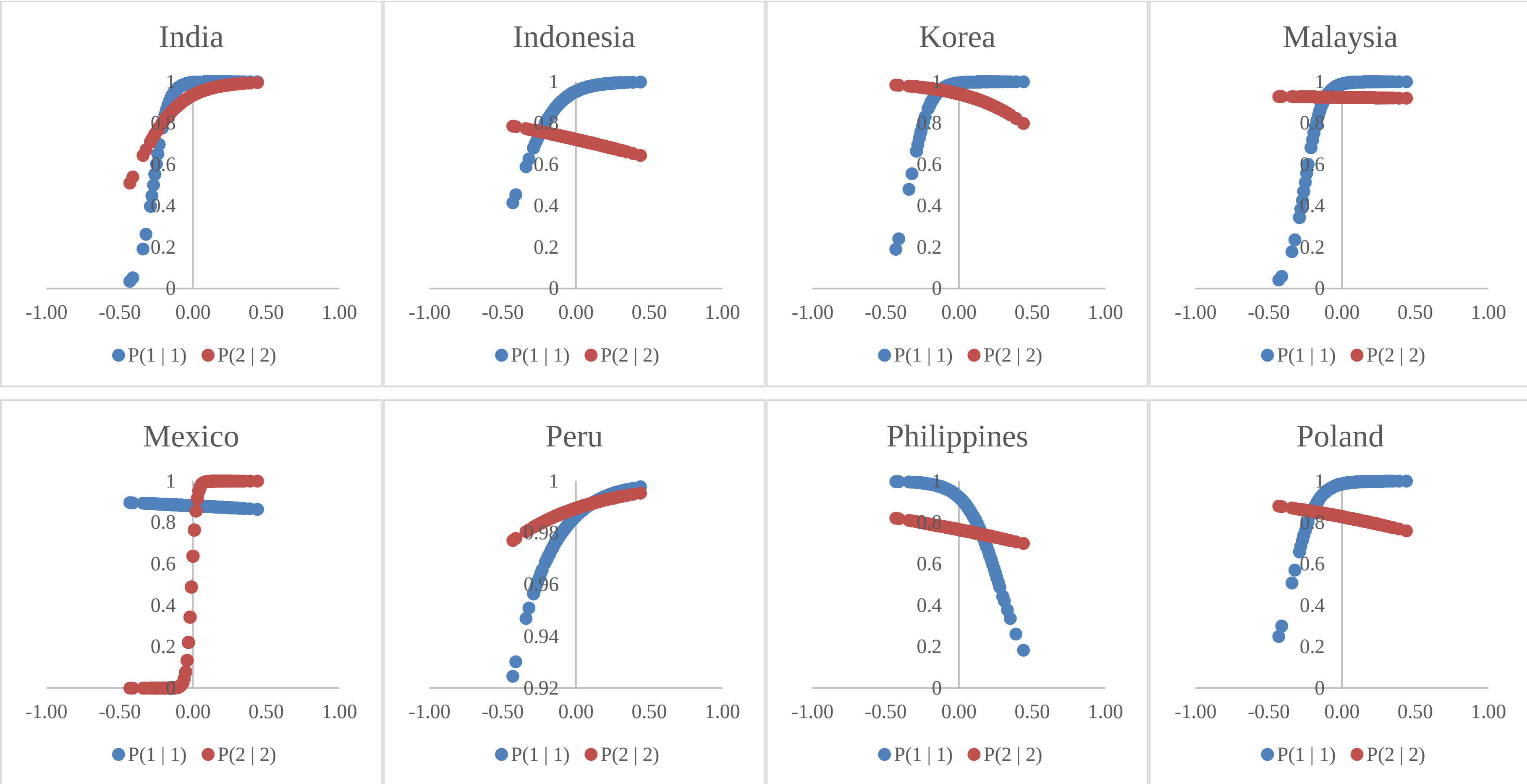

India
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Indonesia
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Korea
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Malaysia
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Mexico
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Peru
1
0.995
0.99
0.985
0.98
0.975
0.97
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Philippines
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)
Poland
1
0.8
0.6
0.4
0.2
0
-1.00 -0.50 0.00 0.50 1.00
P(1 | 1) P(2 | 2)

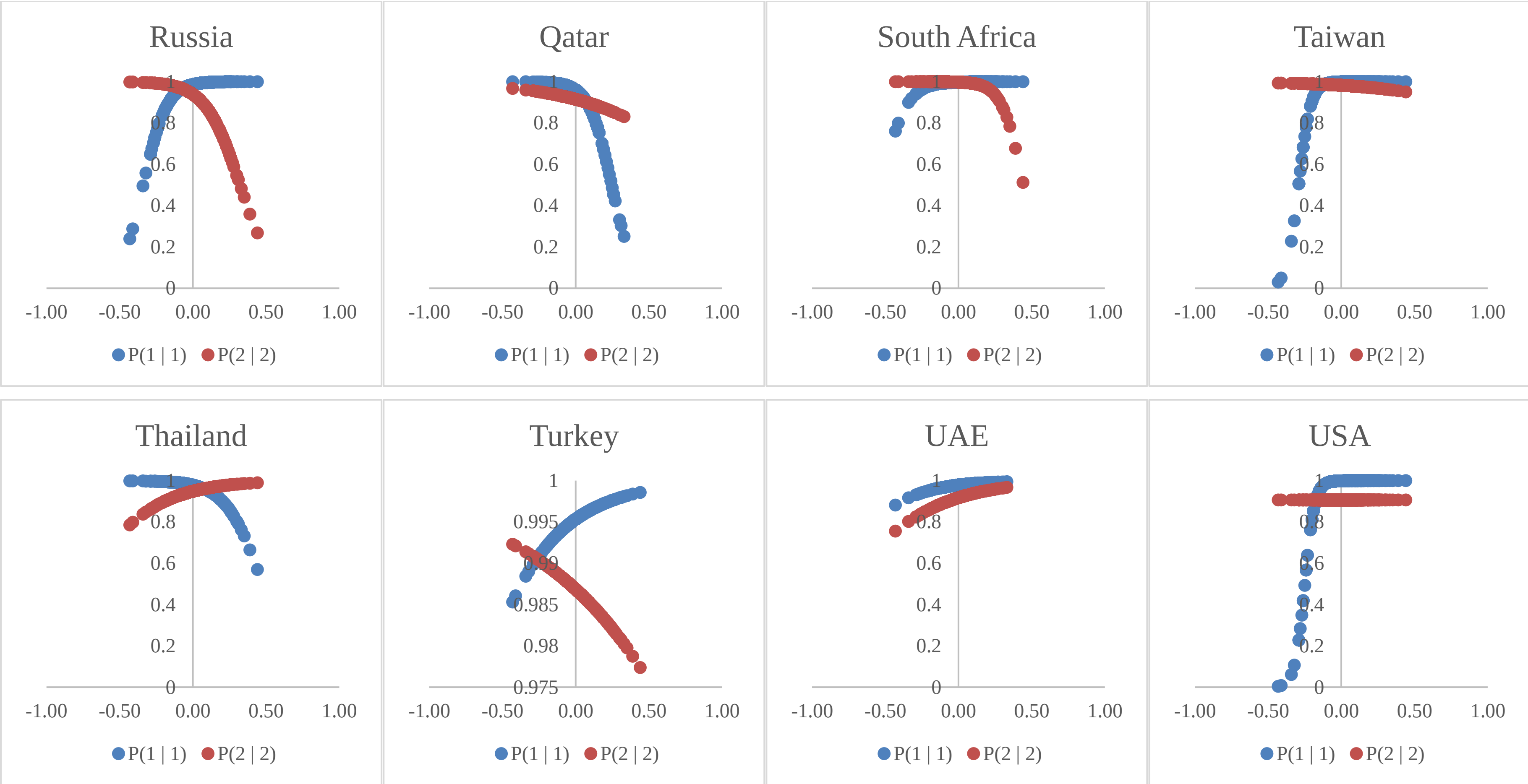


These figures plot the values of p_{11} (blue dots) and p_{22} (red dots) given different values of $\Delta z_{m,t}$, with three-month interest rate differentials on the horizontal axis.

Appendix G Time-varying Probabilities in Emerging Equity Markets and Changes in 5-year US Bond Rate




India
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Indonesia
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Korea
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Malaysia
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Mexico
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Peru
1
0.98
0.96
0.94
0.92
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Philippines
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)
Poland
1
0.8
0.6
0.4
0.2
0
-1.00
-0.50
0.00
0.50
1.00
P(1 | 1)
P(2 | 2)



These figures plot the values of p_{11} (blue dots) and p_{22} (red dots) given different values of $\Delta z_{m,t}$, with the five-year bond differential on the horizontal axis.